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A DISTRIBUTED ARTIFICIAL INTELLIGENCE APPROACH TO INFORMATION FUSION AND OBJECT CLASSIFICATION

Northeast Artificial Intelligence Consortium (NAIC)

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13. ABSTRACT (Maximum 200 words)

The Northeast Artificial Intelligence Consortium (NAIC) was created by the Air Force Systems Command, Rome Air Development Center, and the Office of Scientific Research. Its purpose was to conduct pertinent research in artificial intelligence and to perform activities ancillary to this research. This report describes progress during the existence of the NAIC on the technical research tasks undertaken at the member universities. The topics covered in general are: versatile expert system for equipment maintenance, distributed AI for communications system control, automatic photointerpretation, time-oriented problem solving, speech understanding systems, knowledge base maintenance, hardware architectures for very large systems, knowledge-based reasoning and planning, and a knowledge acquisition, assistance, and explanation system.

The specific topic for this volume is the application of distributed Artificial Intelligence tools to the data fusion and classification problem of modern C3I systems.

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18.1 INTRODUCTION

18.1.1 THE DATA FUSION PROBLEM

Classical signal processing has always relied on the data available from one sensor, which is then utilized for tasks such as detection, classification, identification, estimation and situation assessment. However, more recently, increasing awareness of the use of passive, low-observable sensors supporting active systems such as radar and increased availablility resulting from a remarkable decrease in the cost of the associated hardware has given rise to a trend towards the employment of multiple sensors. Using a variety of methods, such as radio frequency, infrared, and electro-optics which utilize almost the entire range of the electromagnetic spectrum, these sensors can detect, identify and classify objects.

18.1.1.1 PROBLEM BACKGROUND

The merging of diverse data, available as a result of employment of a variety of sensors, into a single sensible representation has emerged as an important issue in today's C3I systems. Data fusion includes the collection, association, aggregation, and merging of data to create and display a coherent representation of current and prior situations. In a sensitive environment, the most crucial aspect is the ability to assess and anticipate an evolving situation. The perception of the situation is a prerequisite for an appropriate response. The resulting increase in the

quantity, quality and rate of information in such systems has dictated the move towards the development of efficient multisensor integration or data fusion approaches.

This move has placed certain requirements on the fusion system. A fusion process should be able to accommodate real world sensors which respond at different intervals and in quite different event spaces. The sensors may be similar or dissimilar, they may provide different types of data, they may have different degrees of accuracy and perception. The information fusion system would need to take into account the quantitative, qualitative or subjective results being provided by the sensors. It must also be able to provide the fused result in more than one output class or event space and in a proper form of representation where the number of different output classes is dependent on the requirements of the user community.

There are a number of advantages of multiple-sensor information fusion These are better performance, survivability, quicker response, reliability, increased dimensionality etc. *Figure 1* lists the major benefits of multiple-sensor data fusion systems over single-sensor systems [1].

18.1.1.2 POSSIBLE APPROACHES

Three main options which one could consider for a satisfactory solution to the problems encountered by the growing need for accurate and timely perceptions (detection and classification) are discussed below.

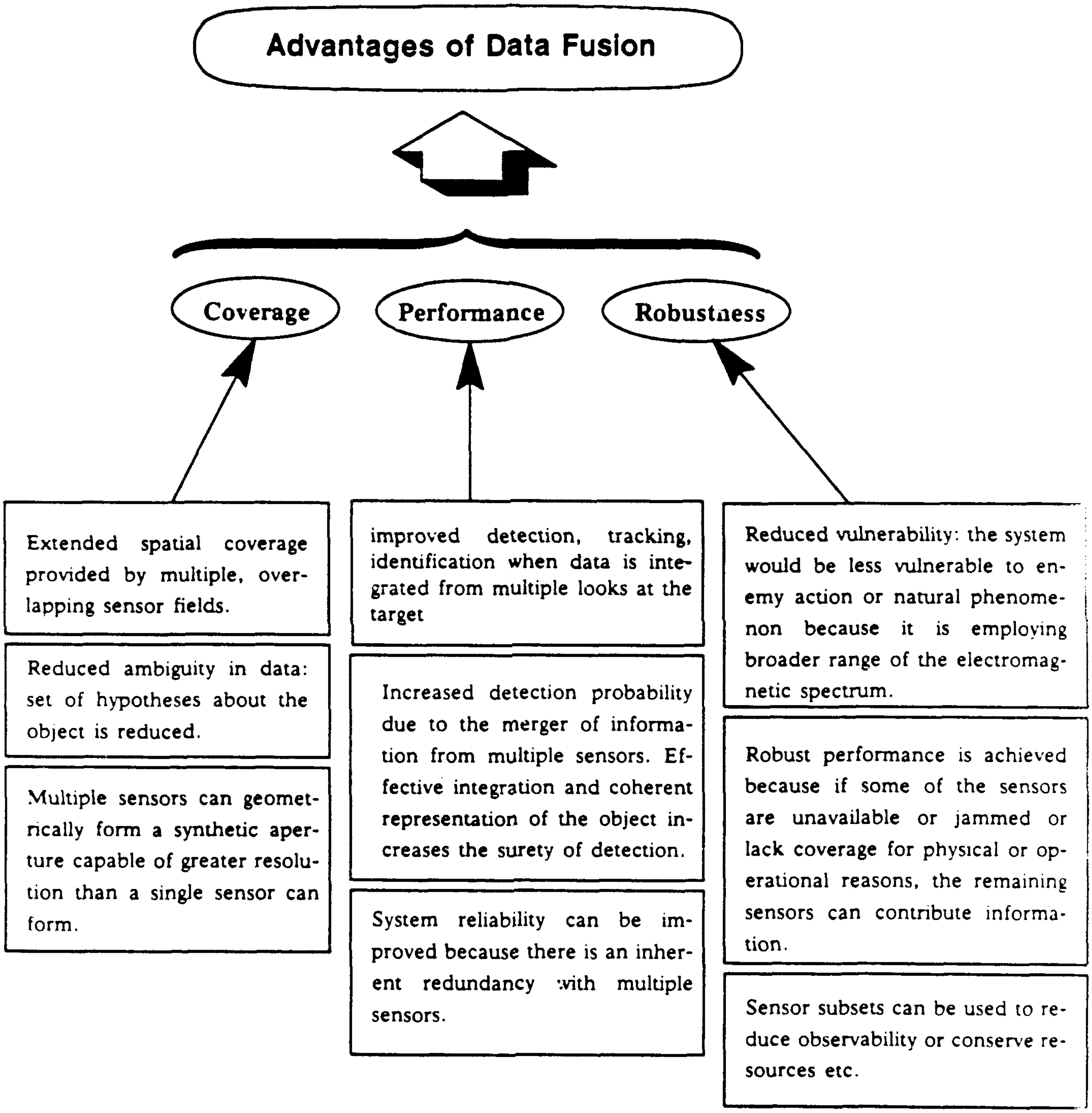


Figure 1 **BENEFITS OF MULTIPLE-SENSOR DATA FUSION SYSTEMS OVER SINGLE-SENSOR SYSTEMS**

The first possibility could be a system that lets a human operator control and monitor data from the sensor bank, and draw appropriate conclusions. The primary advantage of this approach is that the operator or system operator can interpret sensor data in the context of a broad range of situations and experience, which allows him to anticipate certain threats, and ignore those areas which do not seem to be of immediate concern. The drawback is that operator workload quickly becomes unmanageable.

Another approach [2] is to make a hard-wired semiautomatic system by tailoring special-purpose combinations of sensors into "super-sensors." These provide information about a narrow range of situations but lack both the scope and the flexibility to be of more general use.

The third approach could be to build an automatic system that can operate a variety of sensors, and employs artificial intelligence(AI) based techniques to detect objects of interest, integrate, interpret and classify their data, and have the flexibility to adapt to changing situations. The AI based technique would provide means for integrating knowledge and techniques of multiple expert systems, those which have different but possibly overlapping expertise, thereby enabling the solution of problems whose domains are outside that of any one expert system or knowledge source. This approach would combine at least two avenues, a classical statistical approach, and an approach comprising the elements of probability the-

ory and symbolic inference mechanisms. This report is devoted to the description of the development of one such system.

18.1.1.3 LITERATURE REVIEW

An approach to interpret sensor data in the context of a priori models was employed by Garvey and Fischler[2]. Their method can be loosely characterized as the following three step process: anticipate probable threats, plan a sensor utilization strategy and interpret the data returned by the sensors. Techniques for integration of data derived from a collection of sensors, and prior knowledge, in order to assess a hostile air-defense situation[2] can be used to provide up-to-date information about potential ground-based threats to a flight of aircraft attempting to penetrate hostile airspace.

Aircraft ID fusion has been discussed by Vannicola and Mineo[3]. The objective of the program is to develop and demonstrate multisensor aircraft identification fusion processes. It consists of:

i) the a priori data base,

ii) the Source Probability Matrix(SPM) for each of the data sources which measures event characteristics and,

iii) the processing logic which develops and employs the mapping matrices, performs the "fusion" of all single events into a joint event and employs Bayes Theorem for the joint event thereby developing the posterior probability distributions over each of the selected output target classes.

A Bayesian approach has shortcomings in that: no adequate representation of ignorance is allowed within a Bayesian framework. For example, if no information is available concerning two initially exclusive and exhaustive possibilities, in a Bayesian framework, they are usually assigned a probability of 0.5. This is quite different from specifying that nothing is known regarding such propositions. Another problem with a Bayesian approach is the difficulty of ensuring and maintaining consistency in a collection of interrelated propositions. This is because the underlying models from which the point probability values are derived are incapable of supplying such precise data. In these situations, a formal method for integrating knowledge derived from a variety of sources makes use of Shafer's[4] mathematical theory of evidence and is called 'evidential propositional calculus.' Bayesian approach is a special case of this more general methodology. It has the capability of providing for Bayesian inferencing when the appropriate information is available.

Shafer–Dempster logic has been discussed and described by Bogler[5] while placing emphasis on providing realistic examples from the field of multisensor target identification systems and on simulating its operation. His paper and the references contained therein address the questions such as, how evidential information furnished by a knowledge source in the form of a probability distribution can be converted into a form suitable for an application of Shafer–Dempster theory? How multiple bodies of evidential information can be pooled?

A lack of knowledge of the exact conditional probability distributions for the various possible states of evidence and the fact that successful inference networks cannot usually be developed directly from Bayes' rule has also led to the development of another approach, where a hierarchy of "fuzzy" assertions or hypotheses has been developed and used. See Tanimoto [6: Chapter 7] for a very good discussion of the Probabilistic Inference Networks using fuzzy inference rules. These fuzzy inference rules are used to obtain probabilities for other hypotheses, given the evidence.These rules are functions for propagating probability values. The general form is:

$$f : [0, 1]^n \rightarrow [0, 1].$$

Thus, a fuzzy inference rule takes n probabilities as arguments and returns a single probability. The choice of f for a particular situation is a modeling decision that requires some understanding of the relationship among the phenomena described by the hypotheses. He also discusses the updating in inference networks using *Subjective-Bayesian* updating rules and handling uncertain evidence and the Dempster-Shafer calculus. The emphasis in his discussion is on the practical aspects of the data integration problems.

On the other hand, work on the analytical issues of data fusion[7-9] with emphasis on the detection and estimation problem has addressed the hypothesis testing problem in distributed systems with data fusion, optimal decision rules at the detectors, optimal fusion rules for the distributed hypothesis testing problems

using the Neyman–Pearson criterion, the general Bayesian criterion, and the minimum equivocation criterion, to name a few. For details, the reader is referred to the above mentioned reports[7-9] and the references contained therein.

Finally, a highly automated, low-cost, intelligent, distributed sensor network (DSN)[10] might need to address questions like, "What computer network organizational structures are best suited to the situation assessment task?" Two general DSN organizations were tested by the authors; the first was hierarchical and the second was an "anarchic committee" whose nodes could each send messages to one, some, or all other nodes. The performance of the committee organization consistently surpassed the hierarchical one. This indicates that distributed sensor networks should emphasize the cooperative aspects of problem-solving.

In this report, we shall discuss the application of data fusion to the object classification problem which is discussed next.

18.1.2 OBJECT CLASSIFICATION PROBLEMS

18.1.2.1 INTRODUCTION

In the data fusion problems discussed in the previous section, it is desirable to not only detect an object in the field of illumination of a sensor, but also to know something more about the object than its mere presence e.g., the identity of the object may be required. This is where object identification and classification tasks move in. Classification which also appears to be a powerful human strategy for organizing knowledge for comprehension and action is our topic for discussion in this section.

Classification, also sometimes called categorization, as an information processing task is one in which the input is a collection of data about some specific entity e.g., an object, a state, a case, or a situation, and the output is the general category or categories pertaining to the entity. This mapping could be accomplished in a number of ways. The computational complexity of the classification task increases with the increase of the amount of data about the entity to be classified and the number of classification categories.

18.1.2.2 LITERATURE REVIEW

Most of the literature on pattern classification deals with simple (no context) Bayes classifiers. For a broad understanding of various pattern recognition techniques, readers may refer to the books by Duda and Hart[11], Chen[12],

Fukunaga[13], Meisel[14]. For multispectral pattern recognition and classification problems, a very complete survey is given by Nagy[15].

Wu[16] has presented a multistage classification strategy called the decision tree classifier. The decision tree classifier is characterized by the fact that an unknown sample is classified into a class using one or several decision functions in a sequential manner. To achieve the best possible performance with a classifier of this type, the design of the decision stages is of considerable importance. The choice of tree structure and the choice of appropriate feature subsets used at every 'node' will be reflected in the performance (*classification accuracy*) and efficiency (*computation time used*). Wu used a maximum likelihood decision rule at each stage of the tree.

Sands and Garber[17] evaluate a syntactic pattern recognition system for applications to radar signal identification. Three different level-crossing based pattern representation algorithms are considered. The utility of resulting symbolic pattern representations is assessed by evaluating the performance of a maximum-likelihood classifier when the observed symbol strings are used as inputs to the decision algorithm. A syntax analysis algorithm is derived from the likelihood function classifier. Performance results of simulated classification experiments for both maximum-likelihood and language-theoretic classifiers are presented.

The Wald sequential probability ratio test to the discrimination of targets observed by a radar or other sensors was applied by Therrien[18] and a form for the

classifier involving linear predictive filtering was developed.The classifier is based on some well-known results in mean-square filtering theory and has a simple intuitive interpretation. The classifier structure can also be related to auto regressive time series analysis and innovations process concepts and has an interpretation in the frequency domain in terms of the maximum entropy and maximum likelihood spectral estimates for the object signatures. In his sequential approach, a target is illuminated with consecutive pulses until a classification of the target can be made within a prescribed probability of error. Because of the linear-predictive formulation, the computation and storage requirements for the classifier are related only to the number of returns necessary to predict the target signatures and not to the length of signature observed. A classifier with modest storage and computational requirements can be employed to process signatures consisting of an arbitrarily large number of returns.

Ezquerra and Harkness [19] suggested that the simplest classification algorithm is the linear machine, based on Fisher's linear discriminant (FLD) function [11]. In this procedure, the feature vector is reduced from a multidimensional vector to a one-dimensional quantity by summing the weighted features to form one variable; the resultant variable is then compared with a threshold value which determines the classification decision. A second approach is based on the Nearest Neighbor (NN) rule by Duda and Hart [11]. In this approach, feature vectors are stored such that the distances between these stored prototypes and feature vector

of an unknown origin can be calculated. The FLD classifier is faster and simpler than the NN technique. In addition, the latter requires more memory in order to store the prototypes for later comparison. However, the NN technique retains the full dimensionality of the data, thereby allowing the classifier to exploit the characteristics of the underlying probability density functions in the feature space.

Classification of more than two radar targets simultaneously can be accomplished by extending the linear discriminant analysis to the multiple-category case. For a set of R categories: a set of R discriminant functions are constructed, thereby partitioning the feature space into R decision regions. The resulting classifier is a piecewise linear discriminant (PWLD) function, and an unknown feature vector is assigned to the class corresponding to the largest discriminant function. Clustering techniques provide a valuable aid in investigating the inherent characteristics and structure of the object classes. A good discussion of the clustering techniques has been provided in [19].

Rosenfeld[20] has suggested computational techniques that could serve as a basis for object recognition and classification. He has also discussed traditional paradigms for characterizing and recognizing complex classes of objects, and points out some of their serious limitations. Attempt has been made through conjectures at the human way of characterizing object classes and use of parallel hardware has been suggested for rapid recognition of objects. His approach con-

sists of three stages: part segmentation and property value computation, broadcasting and constraint checking.

Welch and Salter[21] laid the basic foundation for contextual pattern classification. They used compound decision theory to introduce contextual information into the decision scheme. Fu and Yu[22] have discussed the compound decision approach to contextual classification and proposed a spatial stochastic model for contextual classification. Interested reader is referred to the book[22] and the references contained therein.

Finally, a very exhaustive review of classification task from the perspective of the knowledge-based reasoning, pattern recognition, and connectionist paradigms in artificial intelligence has been done by Chandrasekaran and Goel [23]

18.1.3 REPORT ORGANIZATION

In this report, a blackboard based *Distributed Artificial Intelligence*(DAI) system is described. Our aim is to describe and demonstrate an artificial intelligence based technique as an answer to today's growing need for automation of information fusion and object classification.

in section.18.2we discuss DAI and why it is suitable for the present day needs of multisensor integration systems. Implementation languages and systems along with blackboard architectures have also been discussed.

Section 18.3 presents the overall system architecture of our DAI system. Use of sensed information as three levels of expert reasoning is discussed. Finally, the organization and operation of the system is presented.

Section 18.4 is devoted to the validation of our system. The concepts and the system presented in the previous chapter are demonstrated by using two knowledge sources which model corresponding sensors supplying the data. Use is made of the data base, generated at the Ohio State University, which consists of calibrated complex (coherent) radar returns measured at various azimuth angles, frequencies and polarizations, along with the ellipticity data. Finally, sample implementation is presented.

To conclude the report the summary of the work done and the possible extensions are presented in section 18.5.

18.2 DISTRIBUTED ARTIFICIAL INTELLIGENCE

18.2.1 INTRODUCTION

Distributed Artificial Intelligence (DAI) is the subfield of artificial intelligence (AI) concerned with concurrency and distribution in AI computations, at many levels. Several recent developments have provoked an interest in DAI: the development of powerful concurrent computers, the widely prevalent computer networks, and the recognition that much human problem solving and activity involves groups of people, schools of thought, and varying degrees of expertise or knowledge.

Elements of an artificial intelligence system are said to be distributed if there is some distance[1] between them [24]. In some domains where AI is being applied, e.g., distributed sensing, medical diagnosis, air-traffic control, knowledge activity in the problem domain is inherently distributed and a DAI solution is highly appropriate. Since information fusion and object classification belong to this domain, after discussing uses and issues related to DAI we shall investigate the possibilities of its application to our problem.

The following are typical rationales for using distribution in artificial intelligence systems.

Adaptability: Logical, temporal, semantic, and spatial distribution allows a

[1] It is meant to be ***conceptual distance***, with respect to some frame such as time, space, semantics, etc.

DAI system to provide alternative perspectives on emerging situations, and greater adaptive power.

Development ease: Each part of the intelligent system could be developed separately by an expert in a particular type of knowledge or domain.

Cost: A DAI system could be cost effective because each unit would be made of components which are simpler and smaller and hence low cost computer systems. However, communication and computing tradeoff has to be considered here, which is discussed later.

Operational speed: Concurrency can increase the speed of computation and reasoning. It may also open up the arena of parallelism.

Ability to treat specialized and dynamic knowledge: Knowledge or action may be collected in specialized, and bounded contexts. It may be represented by experts who have partial view of the entire problem. Addition of specialists for changing situations is no difficult task and hence the system as a whole would be capable of handling dynamic knowledge.

Closeness to the human way of problem solving and management: It is very natural for humans to attack a problem in a distributed form. Most of the organizational structures in the human society also incorporate this principle.

Reliability: Distributed AI systems may be more reliable than are centralized systems because they provide redundancy, cross-checking, and triangulation of results [25].

The major issues involved in the construction of a DAI system can be summarized as follows:

1) the appropriate distribution of subproblems among the processing nodes,

2) the choice of the control strategy in such a way that global coherence is maintained during the problem solving, the knowledge sources are utilized efficiently and optimum performance is achieved.

3) the specification of the communication policies for easy interaction among processing nodes. The processing nodes should cooperate when none of them has sufficient information to solve the entire problem, i.e., each has a partial view of the problem. The sharing of information becomes crucial when the system as a whole is to produce consistent results.

The use of DAI usually reduces the communication bandwidth needed in a distributed processing system, because the nodes communicate only higher-level, which is not so data intensive and is in a more abstract form. The tradeoff between communication and computation should be considered at the time of system design. This is because costs of communication are expensive compared to the costs of computing elements at present.

18.2.2. IMPLEMENTATION FRAMEWORKS & TOOLS

A variety of software tools and frameworks have been developed by the DAI researchers to express solutions to the basic questions of DAI and to enable experimentation with different approaches in different domains. The reasons why we are

concerned with the particular tools currently being used are:

a) research tools help verify theoretical insights through hard, real-world experimentation. So the difficulty of constructing complete theoretical analysis is avoided.

b) the research issues which cannot practically be theoretically modeled due to their complexity can be handled.

c) some tools are designed to express ideas important to the domain and,

d) experimentation is a useful way of getting sometimes surprising results.

An overview of available implementation languages and systems and the blackboard architectures is in order.

18.2.2.1 Implementation Languages and Systems

Any discussion of implementation frameworks and ideas for DAI systems should include the integrative systems and distributed languages which offer great flexibility in problem solving styles and inter-node or inter-agent organization. These provide a way to handle the important area of description and diagnostic mechanisms for DAI systems.

Tokoro and Ishikawa's[26] ORIENT84/K system supplies a language for programming using concurrent objects. In the modeling method proposed by them called DKOM (Distributed Knowledge Object Modeling) a knowledge system consists of a behavior part, a knowledge part, and a monitor part. They have discussed

an expert system built using ORIENT84/K and its performance is compared with some other programming languages/systems.

MACE (Multi-Agent Computing Environment)[27] is a generic testbed allowing the integrated representation of problem solving and communication structures of different grain size and interaction style. MACE "agents" are concurrent objects, consisting of a user-definable procedural part called an *engine*, along with a collection of databases. Designed for experimentation and implementation in a heterogeneous multicomputer environment, the MACE system includes user-controlled tracing and monitoring facilities.

The AGORA environment[28] has been designed as a part of a large speech recognition project. It allows the integration of multiple languages and highly parallel computations. Another architecture, ABE [29] supports the integration of collections of independent cooperating problem solving components of several different grain sizes and problem-solving styles. ABE processors can manage resources locally, because resources are passed with control flow among modules.

A family of languages known as *distributed, object oriented languages* (DOO languages)[24] is a natural framework for implementing concurrent DAI systems. Message communication allows interobject interaction in these languages. The objects are the building blocks with data and procedural abstractions of objects being described. Language processors and underlying kernels implement allocation, load balancing, addressing and message-routing schemes invisible to the programmers.

18.2,2.2 Blackboard Architectures

Blackboard architectures have become a popular paradigm for developing knowledge-based systems and are becoming a mainstay of many projects in DAI. Conventional blackboard architectures incorporate a shared common data area or *blackboard* as the common medium for memory and interaction among a collection of *knowledge sources*. A blackboard architecture instantiates a three step process:

1) Identify the set of permissible next computations

2) Select the next computation from among the permissible computations

3) Execute the selected computation.

The collection of knowledge sources may read and write on one or more levels, under the supervision of a *control system*. Control in typical blackboard systems is sequential and organized by a centralized scheduler, but the knowledge sources work with semantically disparate rules or procedures. It may also be a system of concurrency locks, or a collection of integrated control-knowledge sources.

The use of blackboard based architectures for the implementations of DAI systems has been quite widespread. The blackboard architectures were introduced for the first time in Hearsay Speech Understanding System[30]. The functional independence of knowledge sources, flexibility in the choice of control strategy, and the structuring of blackboard information make blackboard architectures a powerful yet flexible framework for a knowledge-based application. The interest in the generic control architecture of BB1[31] and GBB[32] are examples of increas-

ing popularity of blackboard architectures. The blackboard paradigm may be simple to describe but is difficult to implement effectively for a particular application. Nii [33] has noted that the blackboard model with its knowledge sources (KSs), global blackboard database, and control components doesn't specify a methodology for designing and implementing a blackboard system for a particular application. A more detailed discussion of the blackboard structures implemented todate along with their features and operational details follows.

18.2.3 BLACKBOARD STRUCTURES: A LITERATURE REVIEW

The speech understanding system, Hearsay II[30], developed at the Carnegie Mellon University(CMU), was the first ever system to employ blackboard based architecture. In this system, the KSs have been developed to perform a variety of functions, such as extraction of acoustic parameters, classification of acoustic segments into phonetic classes, recognition of words, parsing of phrases, and generation and evaluation of predictions for undetected words or syllables. The blackboard is subdivided into a set of information levels corresponding to the intermediate representation levels of the decoding processes (phrase, word, syllable, etc.). Each hypothesis resides on the blackboard at one of the levels and bears a defining label chosen from a set appropriate to that level e.g., the word FLYING, the syllable ING, or the phoneme NG. The hypothesis contains additional information, including its time coordinates within the spoken utterance and a credibility rating. The sequence of levels on the blackboard forms a loose hierarchical structure,

hypotheses at each level aggregate or abstract elements at the adjacent lower level. The possible hypotheses at a level form a search space for KSs operating at that level. Top down and bottom up problem solving behaviors can be accommodated simultaneously by a HEARSAY II KS.

At the start of each cycle, the scheduler, in accordance with the global state information, calculates a priority for each activity (KS condition program or action program) in the scheduling queues. The highest priority activity is removed from the queues and executed. If the activity is a KS condition program, it may insert new instances of KS action program, the blackboard monitor notices the blackboard changes it makes. Whenever a change occurs that is of interest to a KS condition program, the monitor creates an activity in the scheduling queues for that program. The monitor also updates the global state information to reflect the blackboard modifications.

Yang and Huhns[34] say that establishing a problem solving hierarchy in a distributed environment requires that planning and problem solving be combined with internode communications. Problem solving by their system occurs as an iterative refinement of several mechanisms, including problem decomposition, kernel-subproblem solving, and result synthesis. They suggest the following capabilities at the processing node:

i) *Intranode communication facility* that allows different processes at the same processing node to share information.

ii) *Dynamic planning ability*, which adjusts the problem solving (PS) plan and guides it by either actual calculations or estimation, in the most promising direction based on the latest PS status.

iii) An *internode communication facility* that permits the different processing nodes to share tasks and results.

iv) *Problem deduction ability* that solves tasks by invoking required knowledge sources.

v) A *learning ability* that enables the system to change its organization and improve its performance as more PS experience is obtained.

Their black board is chiefly used for internode communication. It is an active data structure located at each processing node and it allows information sharing by storing tasks, plans and partial results and transmitting them at appropriate times in the PS process. Also, a means for sharing information about different PS processes within the node.

In her paper, Hayes-Roth[31] looks into the "blackboard control architecture". Her work has explicated and provided mechanisms for solving control problems such as independent generation of desirable and feasible actions and reconciliation, the prioritization of action, and the dynamical planning of useful sequences of actions.

A blackboard architecture designed for the distributed environment of a network of heterogeneous computers, COPS[35], has rule-based blackboard proc-

esses which are also internally sequential. They can be notified of remote events on each other's blackboards using "ambassadors," which are simply local rules that represent the interests of remote processes.

The GBB (Generic Blackboard)[32] is a high-level implementation tool designed to provide an application builder with both speed and flexibility in implementing a blackboard-based application as well as an efficient execution capability. GBB contains two distinct subsystems: a high-level blackboard database compiler and a set of generic control shells. The blackboard architectures have suffered from limitations such as difficulty in implementation, lack of portability and generality and clumsy information placement and retrieval schemes. The effort made at the University of Massachusetts at Amherst is to overcome these shortcomings and is noteworthy in this regard. The organization of GBB is shown in *Figure 2*. The blackboard database compiler defines the blackboard and blackboard objects as well as the insertion retrieval and storage structure. The generic control shells define the KSs, and also create other control objects such as goals or plans. Three different control schemes are available in the GBB, simple shell control shell, KS and execution shell and the Knowledge Base(KB) shell where the latter two are based on the BB1 model of control. As noted earlier, the compiler and control shell are two distinct subsystems with the blackboard events signifying any change in the situation.

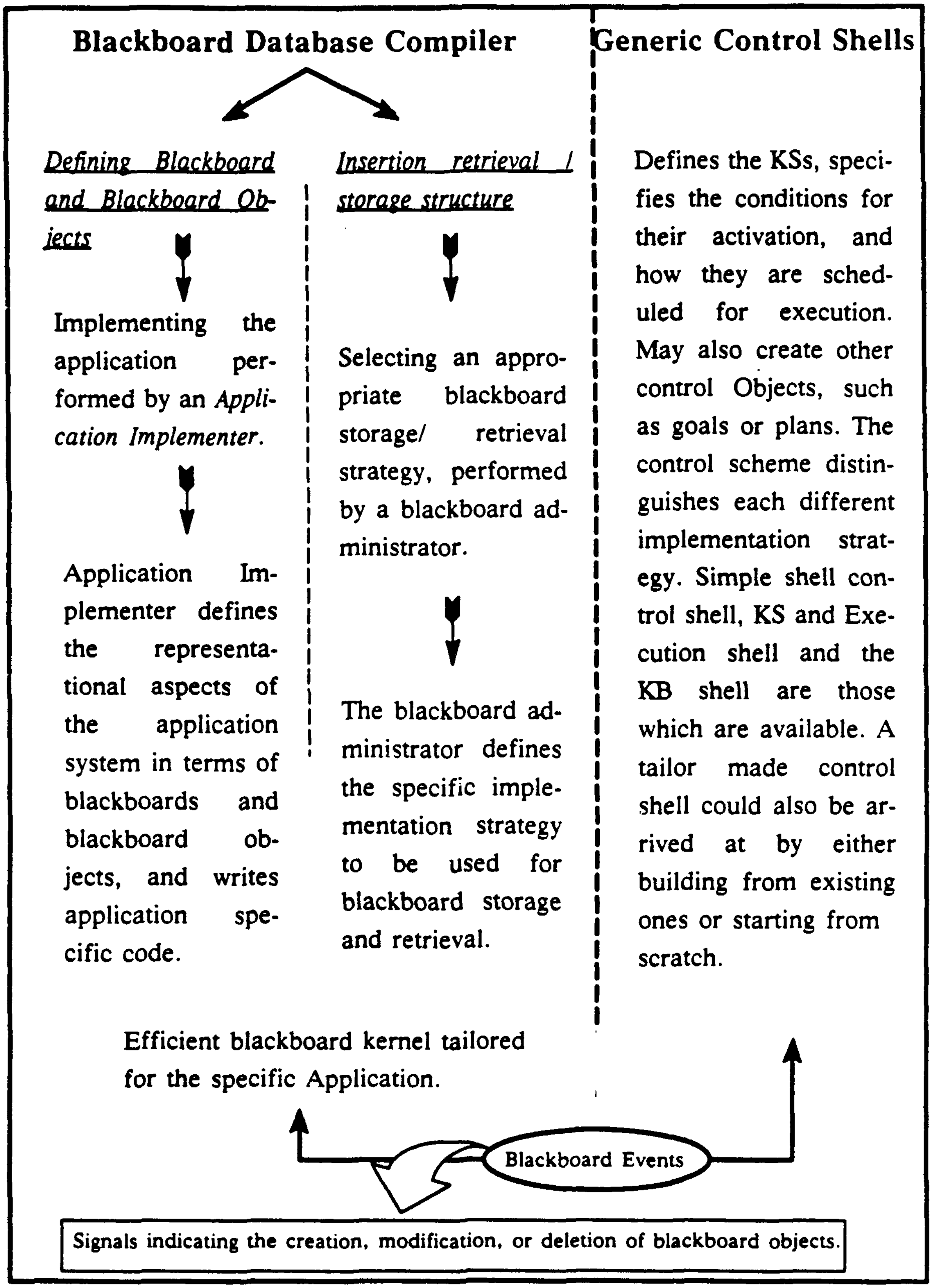


Figure 2 ORGANIZATION OF THE GBB

18.2.4 SUMMARY

Distributed Artificial Intelligence (DAI) can potentially solve problems that are too large for a centralized system because of resource limitations induced by a given level of technology. Limiting factors such as communication bandwidths, computing speed, and reliability result in classes of problems that can be solved only by a distributed system. It can provide means for interconnecting multiple expert systems that have different, but possibly overlapping expertise, thereby enabling the solution of problems whose domains are outside that of any one expert system or knowledge source. DAI is the most appropriate solution when the problem itself is inherently distributed, such as in distributed sensor nets, distributed information retrieval and knowledge acquisition, because it is easier to find experts in narrow domains. Many problem domains are already partitioned or hierarchical as in the object detection case, and that is why DAI lends itself easily to it. Our research is aimed at using DAI for the solution of object classification problem in a data fusion system with distributed sensors.

18.3 OVERALL SYSTEM ARCHITECTURE

In the first chapter, we talked about the need for automation of the multisensor data fusion with emphasis on the object classification problem. This need has provided the fuel for the investigation of the DAI techniques which could be applied for the implementation of such systems. The present chapter is devoted to the description of the system architecture proposed in this research.

18.3.1 BACKGROUND

The purpose of the system is the processing of sensed data available from multiple sensors about a single object. The main goals are to:

1) Combine it into a single useful report or, in other words, a coherent representation of the situation, and

2) Perform classification by its features into disjoint sets (object classes). Our system is fairly general to incorporate any kinds of objects and classification schemes as well as categories.

Figure 3 shows the sensor input model to the data fusion center. As illustrated many sensors and distributed sensor networks feed in the information in the form of reports to the *data grouping and compaction* unit, which also receives the contextual information and intelligence data. The different kinds of information and measurements form the basis of expert system reasoning, which is discussed later

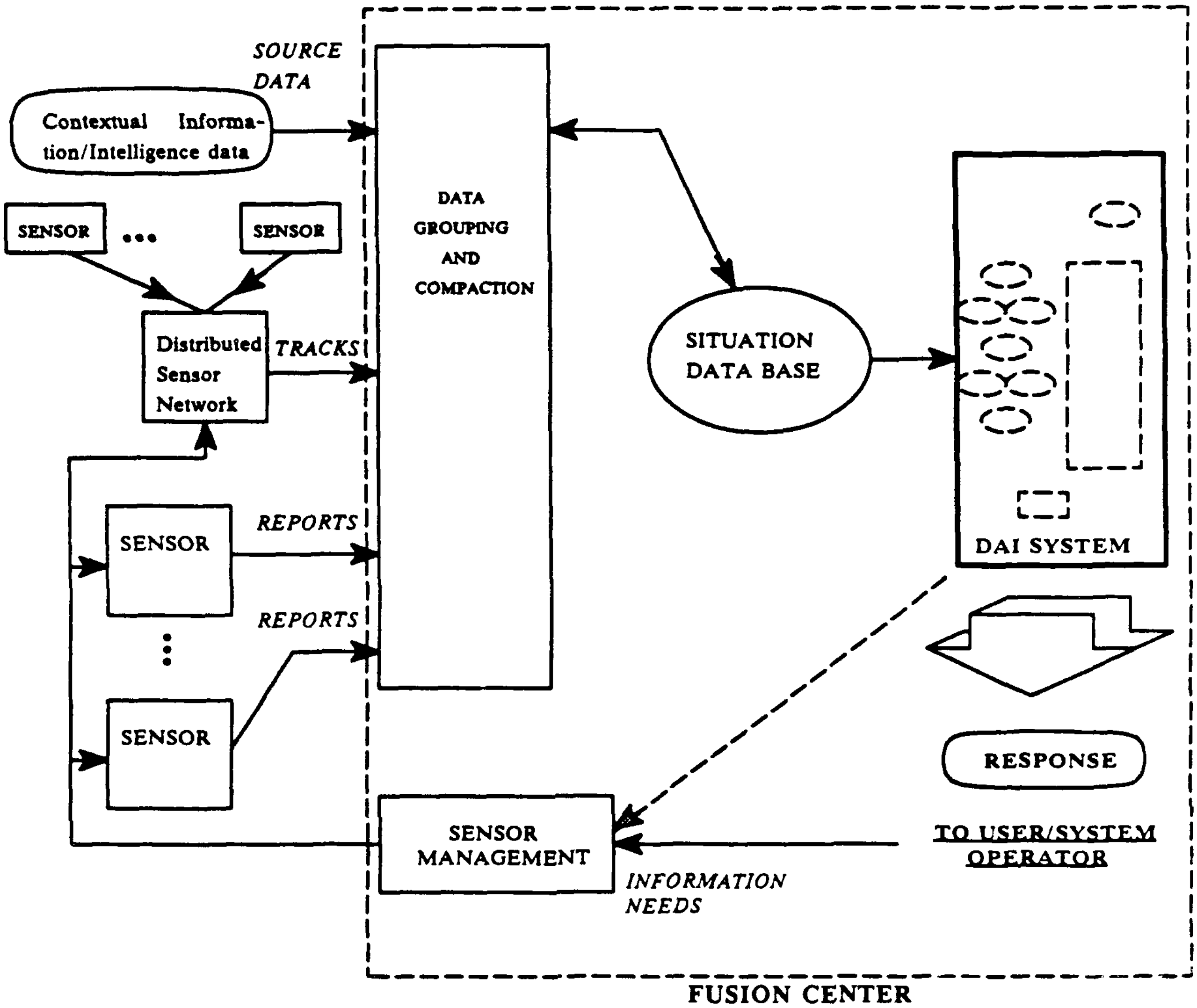


Figure 3 SENSOR INPUT MODEL TO THE DATA FUSION CENTER

Note: the broken arrow indicates the flow of action in case of a fully automated system.

In section 10.3.2 The detailed description of *data grouping and compaction* unit is beyond the present scope, but for the present discussion it would be sufficient to say that it eliminates the redundant or unimportant data and groups the data in the form of packets with each scan. In other words, it defines the boundaries between the scans, and maintains some form of organization. It also maintains data about the events which do not require immediate attention and can wait or those that are expected to happen. These events are called *simple events* and *expected events* respectively. The ones which require immediate attention are called *clock events*. The situation data base exchanges the data with the data grouping and compaction unit with the highest priority to the clock events.

The DAI system extracts the information from the situation data base and outputs the *object identification theory* to the user/system operator who, in turn, performs sensor management. As noted earlier, in a fully automated system the flow of action would not include the user/system operator except for the purpose of informing him of the decision and the chosen course of action.

In general, for a data fusion problem three criteria drive the design of any "reasonably intelligent" object identification/classification system. These include the following.

1) *Sensor Modeling:* Each sensor is unique to itself so it is likely to be contributing information to the situation data base in its own sensor-specific level of abstraction. The system should be capable of accurately modeling the information pro-

vided by each sensor source.

2) *Data Fusion and interaction with the user:* The system must be capable of:

i) fusing the information provided,

ii) computing a statistical or probabilistic or fuzzy measure for the resultant ID and classification quality, and

iii) accurately displaying the information to the user. This information should be explicit and there must be provisions to the user/system operator/battle commander to specify his own set of parameters which guide the operation of the system. This is to provide the system with the maximum amount of situation and contextual knowledge along with the common sense and experience which is so exclusively human!

3) *Conflict Resolution:* The system should be capable of resolving any potential sensor conflicts or failures. In other words, the combining mechanism should be capable of giving a decision and issuing a warning (if necessary) to the user or system operator that the confidence in the object identification theory is not enough, and it might be dangerous to pursue it any further.

18.3.2 USE OF SENSED INFORMATION

The process of data fusion uses a combination of sensors and sources to collect information of the tactical situation. This information might include: reports of

object detections, related events, tracks, or factual information. This data is used to detect, locate, and classify the objects and events.

Figure 4 shows the three levels of expert reasoning which are used to obtain discrimination between objects of similar type or discrimination between objects of different types (i.e., identification). This can be achieved by any one or a combination of sensed variables. The discrimination process can infer the identity by measured object attributes, object behavior, or contextual clues provided by multiple sensors.

Directly measured features[1] include attributes of the object e.g., spectral signatures: radar, IR etc., spatial characteristics, or of the phenomena that can be associated with the object e.g., effects on the environment, secondary effects, or events linked to the object. These attributes are measured by the sensor directly or result from preprocessing operations (filtering, integration, clustering), which refine and combine the raw measurements into a single attribute.

Behavioral/Derived measurements of the object include temporal behavior (velocity, acceleration, maneuvering, direction of travel, etc.), tactical activities (emitter status/mode, and hostile or friendly acts such as jamming, deceptive, or engagement actions) and ellipticity measurements. Doctrinal procedures can be established to permit behavior to be independent of object performance and to allow unique object discrimination. Examples are air corridors and restricted zones, which provide discrimination of foes by restricting the behavior of friends.

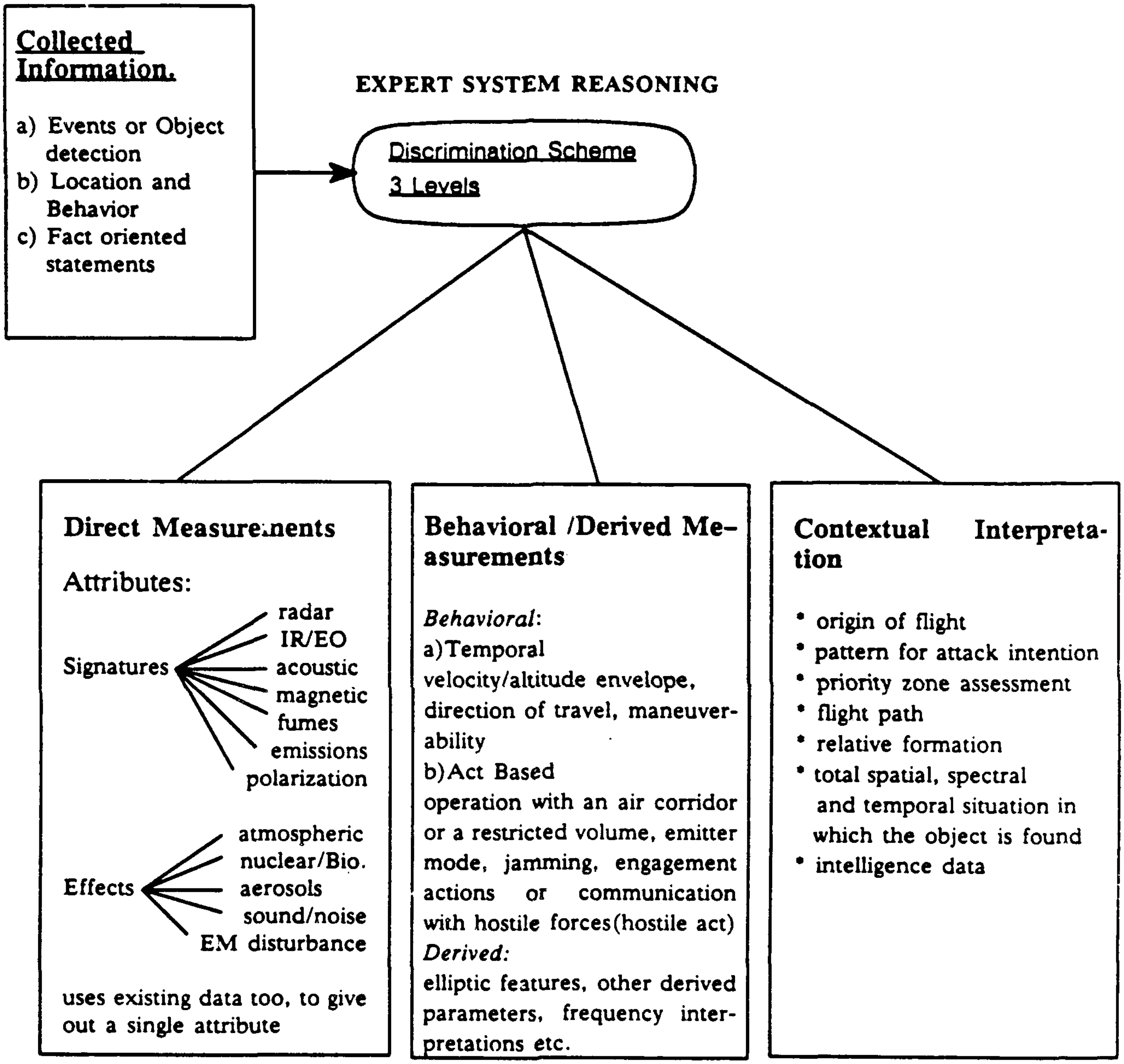


Figure 4 THREE LEVELS OF EXPERT REASONING

Contextual interpretation implies the total spatial, spectral, and temporal situation in which the object is found. The location and relationship to other objects; and the background information constitutes the spatial context e.g., priority zone assessment and pattern for attack intention. The spectral context includes sensed attributes e.g., communication, countermeasure activities, levels of noise. Temporal context information includes the relative timing of sensed events or object activities and their implications of coordinated group behavior.

18.3.3. THE SYSTEM ORGANIZATION & OPERATION

The combination/classification mechanism of our system combines heuristic and statistical pattern recognition technique. It requires parametric knowledge of apriori probabilities for the combination scheme and assumes independence of measured values.

The key functions of generating, interacting with the user and posting hypotheses on the blackboard are performed by diverse and independent programs called *knowledge sources* (KSs). Each KS can be roughly schematized as a condition–action pair. The condition component prescribes the situations in which the KS may contribute to the problem–solving activity, and action component specifies what that contribution is and how to integrate it into the current situation. KSs have been developed to perform a variety of functions and are capable of accounting for inaccurate or insufficient data. If one of the KS is not able to post a hypothesis then the PS activity continues on the basis of the other KS only and the system

warns the user that the object identification theory might be unreliable and should not be pursued any further, since the results would not help the system operator but instead they might lead to decisions which might not be suitable.

KSs communicate with each other through a blackboard as shown in *Figure 5.* It is a global database, which records the hypotheses generated by KSs, combines them and has a confidence KS built into it that informs the user of the overall confidence in the object identification theory and whether it should be pursued any further. Refer to the section on the probability basis for more about the scheme employed for the combination mechanism in the sample implementation. Any KS can generate a hypothesis and post it on the blackboard. These actions, in turn, may produce structures that satisfy the applicability condition of the other KSs. In our framework, the blackboard serves four functions: it performs KS initiation, represents intermediate states of problem-solving activity in the form of levels with the posted hypothesis of each KS, it communicates messages from one KS that activate other KSs and it combines the hypothesis from the KSs to report a best explanation or refined hypothesis which then is tested for the overall confidence before being reported to the outside world as an object identification theory.

The system which we have described in this section is implemented on a serial machine, Symbolics 3645, but it simulates the concurrent communication and processing of a distributed system.

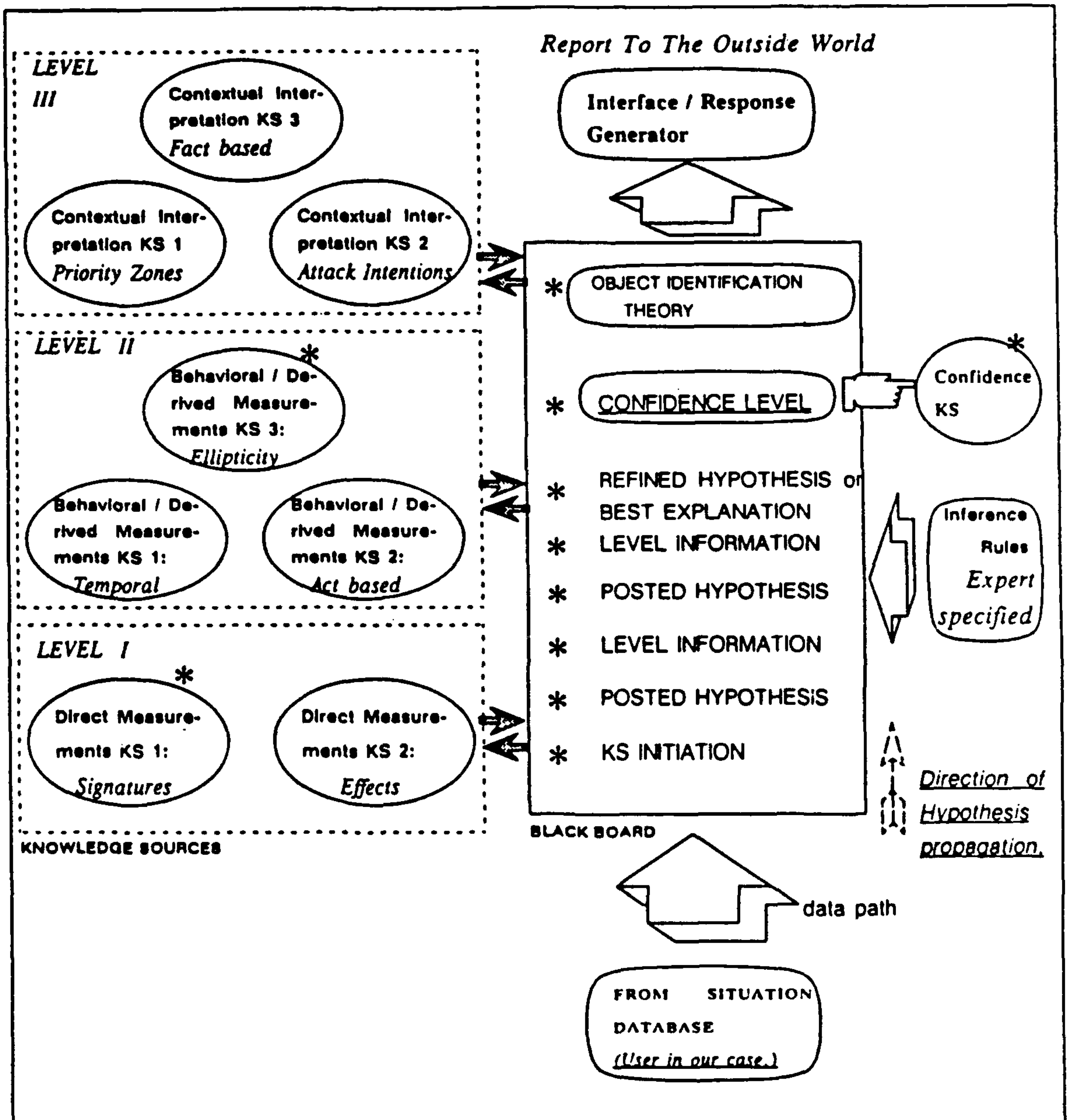


Figure 5 A BLOCK DIAGRAM OF SYSTEM ORGANIZATION

It accepts all the data from the user at one time, in one scan, thus modeling many sensors pouring in the information together. Each knowledge source picks up the relevant data or posted guess and performs the necessary computations. If it cannot generate a satisfactory hypothesis, it keeps on interacting with the user till a guess can be made or the user declares that he doesn't have sufficient data. This delay in posting the hypothesis on the blackboard, is to delay the communication till computation has been performed to a satisfactory level, hence minimizing the cost.

A unique feature of our system is that KSs at one level 'can know' the hypotheses, posted on the blackboard, by other KSs of the same level. In other words, they can read it from the blackboard. However, to avoid any bias towards the decision of object identification theory, KSs at different levels (except the contextual interpretation KSs) will proceed independently to generate and post their hypotheses. The combination and decision making is left on the knowledge built into the blackboard.

The contextual interpretation KSs shall only be able to add or subtract confidence in object identification theory and inform the user/system operator of its significance, consequence and implications. They cannot modify or delete it.

The system implementation and validation of our system is discussed next.

18.4 SYSTEM VALIDATION

To solve object identification and classification problem, using the system presented earlier we utilized five commercial ACs as objects and modeled the sensors using two Knowledge Sources(KSs), for aspect angle with polarization and the ellipticity information. In the present chapter, we demonstrate the feasibility of our architecture using a data base which is a subset of the expert reasoning mentioned earlier. The description of this data base is the topic of the following sections.

18.4.1 BACKGROUND

The objects to be identified and classified in our system are Aircrafts(ACs). The category of the ACs is commercial and they belong to one of the five classes: Boeing 747, DC10, Boeing 707, Concord, and Boeing 727. The knowledge sources of our system utilize the data in the form of tables which was gathered through experimentation at The Ohio State University (OSU). OSU ElectroScience Laboratory (ESL) has developed various methods for solving the Radar Target Identification (RTI) problem [36]. Areas of research have included the investigation of optimal frequency ranges [37], where wavelengths extend from the Rayleigh region to the optical region, and polarization studies [38] involving various linear and non-linear combinations of the radar scattering coefficients.

Before discussing the KSs of our system, some electromagnetic theory background is in order.

The optimal frequency range for radar target identification should lie in the Rayleigh - resonance frequency range where the wavelength is about the same size or larger than the size of the target (we shall call it object henceforth) [39]. So in this region the scattered field is descriptive of the shape and volume of the object. In the resonance region the scattered field is due to re-radiating surface currents set up on the object body and also gives the object shape and size information. The desired features for object identification are found; the character of the radar return is not influenced appreciably by the shape and size information and small changes in aspects.

However, in the optical region, where the wavelength is small compared to the object size, small changes in aspects can cause significant changes in the scattering characteristics. The scattering mechanism in the optical region are related to the interaction of the specular points and contain information on the finer details of the object. Small changes in aspects cause significant changes in the scattering characteristics, if the separation of the specular points is large compared to the incident wavelength.

18.4.2 MODELING THE SENSORS

The ESL has developed a multi-frequency data base [36] consisting of ocean ship, aircraft, and ground vehicle radar signatures, and has explored radar detec-

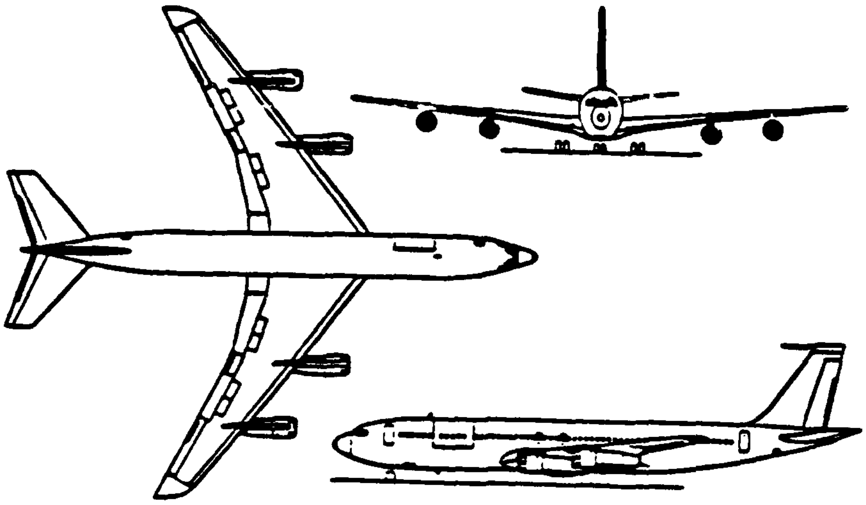
tion methods and various classification methods for each class of objects. We are utilizing this data base as tables for each kind of sensor, which is being modeled by a KS. In a real life situation, these entries would be extracted from the situation data base, replacing the user who is currently responsible for supplying the data to the system.

The feature space contains the information available in the electromagnetic energy return from the scattered object. Information available from this energy spectrum depends on both the transmitter and the scatterer. Features such as transmitted frequency, received amplitude, transmitted polarization, received polarization, and object range, are available to most radar systems. There can be other features too, such as received phase, object speed, object direction etc. The reader is referred to the three levels of expert knowledge; direct measurements (DM), behavioral/derived measurements (BM), and contextual interpretation (CI) described earlier.

The two measurements which we utilize are the direct measurements (aspect angle, polarization data) and the derived measurements (ellipticity data). The description of the features of the data utilized and how they were obtained are the contents of the following discussion.

18.4.2.1 Aspect angle, polarization data

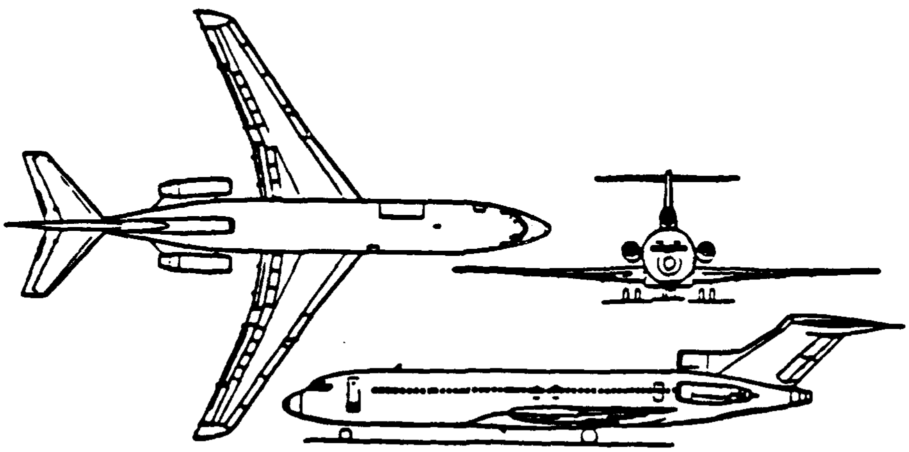
The data base we use consists of calibrated complex monostatic radar returns from five metallic coated scale model aircraft: Concord, DC10, Boeing707,



External Dimensions:

Length overall	152 ft 11.0 in (46.61m)
Height overall	42 ft 5.0 in (12.93m)
Wing span	145 ft 9.0 in (44.42m)

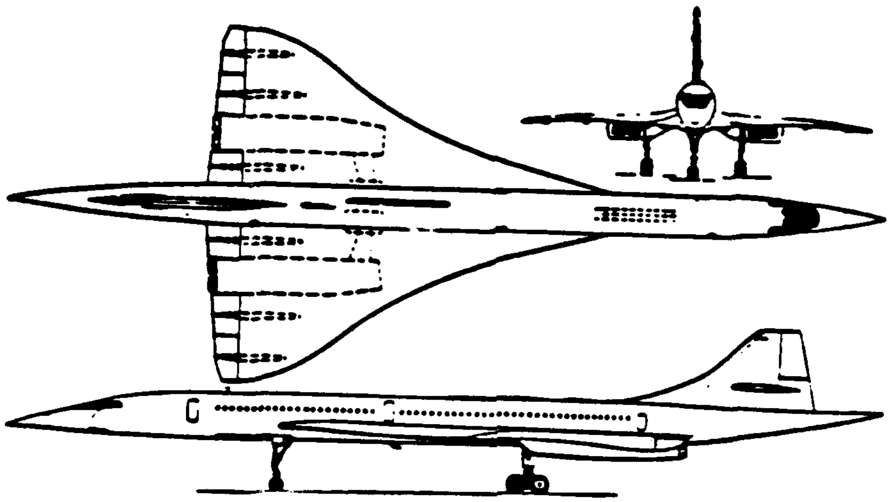
Figure 6 707 Silhouette and Physical Data



External Dimensions:

Length overall	153 ft 2.0 in (46.69m)
Height overall	34 ft 0.0 in (10.36m)
Wing span	108 ft 0.0 in (32.92m)

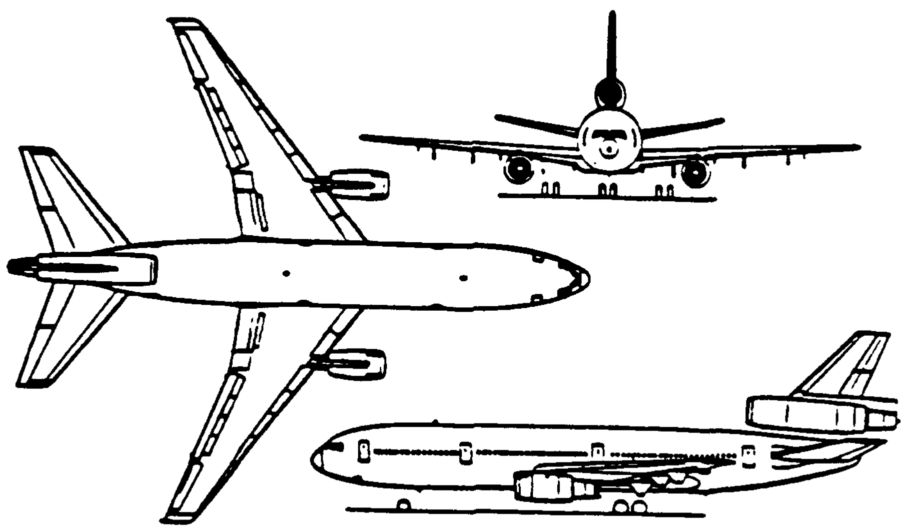
Figure 7 727 Silhouette and Physical Data



External Dimensions:

Length overall	202 ft 3.6 in (61.56m)
Height overall	40 ft 0.0 in (12.19m)
Wing span	83 ft 10.0 in (25.56m)

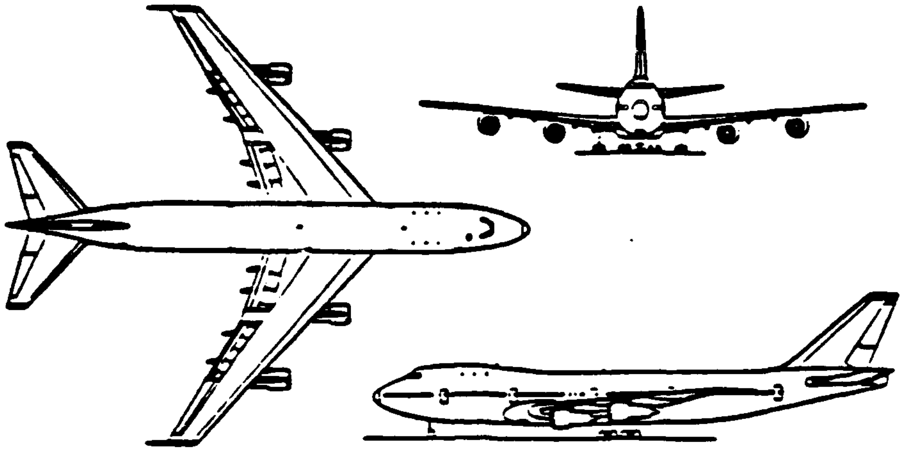
Figure 8 Concord Silhouette and Physical Data



External Dimensions:

Length overall	181 ft 7.2 in (55.35m)
Height overall	57 ft 7.0 in (17.55m)
Wing span	165 ft 4.8 in (50.39m)

Figure 9 DC10 Silhouette and Physical Data



External Dimensions:

Length overall	231 ft 4.0 in (70.51m)
Height overall	63 ft 5.0 in (19.33m)
Wing span	195 ft 8.0 in (59.64m)

Figure 10 747 Silhouette and Physical Data

Boeing727, and Boeing747 [36]. The silhouettes and the full-scale dimensions of these commercial aircraft are shown in *Figures 6–10*. The data base consists of calibrated complex (coherent) monostatic radar returns measured at various azimuth angles, frequencies, and polarizations, at an elevation and roll angle of 0 degree. The data was taken at the OSU ESL compact range facility [40] over the frequency bands of 1 to 12 GHz. The polarization schemes measured are listed below as polarization types:

(HH) Transmitting Horizontal polarization, Receiving Horizontal polarization.

(VV) Transmitting Vertical polarization, Receiving Vertical polarization.

(HV) Transmitting Horizontal polarization, Receiving Vertical polarization.

The polarization types HH, VV are commonly referred to a co-pol polarizations, and the polarization type HV is referred to as the cross-pol polarization. Note that by the electromagnetic theorem of reciprocity, the polarization types VH (Transmitting Vertical polarization, Receiving Horizontal polarization) and HV are equal. Additional steps[41] are required to obtain the "low-error" signature. The purpose is to remove unwanted background clutter from the object measurement and provide a scale correction factor based on a mathematical representation of a reference object. Calibration equations are used and to ensure the best results in the calibration process, background and reference object measurements are made after every five object measurements. Additional signal processing techniques are employed to achieve the final form of the low-error object backscattered signature.

Finally, a computer program called DATABASE [42] allows the storage of frequency formatted data strings at many different aspect angles and the three base line polarization types HH, VV, and HV, into one single random-accessed data file. Listings from the DATABASE computer program characterizing the RTI aircraft data bases as shown in *Table 1-5* are used as the knowledge base for the Aspect angle Polarization (ASPOL) KS.

18.4.2.2 Elliptical Features

The concept of transient polarization impulse response (TPIR) is used [43]. It could possibly be used to identify radar objects based on a decomposition of the return signature into portions that correspond to object substructures, such as wings, tails, or engine inlets. Conceptually, the TPIR can be envisioned as the result of transmitting a short circularly polarized (CP) pulse toward the radar object, and then measuring the back-scattered response with (wide band) vertically and horizontally polarized antennas. If the outputs of the vertical and horizontal antennas were connected to the *y* and *x* plates of an oscilloscope, the TPIR would be observed.

There are possibly many ways of parameterizing the polarimetric information contained in TPIR in a form usable by the pattern recognition components of an object identification system. An effective parameterization technique is known as the "ellipse fitting"[43]. From *Figure 11* it may be observed that subsections of the "end view" of the TPIR closely resemble ellipses or partial

The Ohio State Univesity ElectroScience Laboratory
Compact Range Experimental Data 1984
Scale factor =   Elevation angle = 0 degrees

LOW FREQUENCY FORMATTED DATA BASE (GHz)

ASPECT (Deg)	POLARIZATION " HH "	" HV "	" VV "
0	1-12	1-12	1-12
10	1-12	1-12	1-12
15	1-12	1-12	1-12
20	1-12	1-12	1-12
30	1-12	1-12	1-12
40	1-12	1-12	1-12
45	1-12	1-12	1-12
50	1-12	1-12	1-12
60	1-12	1-12	1-12
70	1-12	1-12	1-12
75	1-12	1-12	1-12
80	1-12	1-12	1-12
90	1-12	1-12	1-12
100	1-12	1-12	1-12
105	1-12	1-12	1-12
110	1-12	1-12	1-12
120	1-12	1-12	1-12
130	1-12	1-12	1-12
135	1-12	1-12	1-12
140	1-12	1-12	1-12
150	1-12	1-12	1-12
160	1-12	1-12	1-12
165	1-12	1-12	1-12
170	1-12	1-12	1-12
180	1-12	1-12	1-12
270	1-12	1-12	1-12

Figure 1   727 Low-Frequency Data Base Map

The Ohio State Univesity ElectroScience Laboratory
Compact Range Experimental Data 1984
Scale factor =   Elevation angle = 0 degrees

LOW FREQUENCY FORMATTED DATA BASE (GHz)

ASPECT (Deg)	POLARIZATION " HH "	" HV "	" VV "
0	1.5-12	1-12	1-12
10	1.5-12	1-12	NULL
15	6-12	1-12	1-12
20	1.5-12	1-12	NULL
25	6-12	NULL	NULL
30	1.5-12	1-12	1-12
35	6-12	NULL	NULL
40	1.5-12	1-12	NULL
45	1.5-12	1-12	1-12
50	1.5-12	1-12	NULL
55	6-12	NULL	NULL
60	1.5-12	1-12	1-12
65	6-12	NULL	NULL
70	1.5-12	1-12	NULL
75	6-12	1-12	1-12
80	1.5-12	1-12	NULL
90	1.5-12	1-12	1-12
95	6-12	NULL	NULL
100	1.5-12	1-12	NULL
105	6-12	1-12	1-12
110	1.5-12	1-12	NULL
115	6-12	NULL	NULL
120	1.5-12	1-12	1-12
125	6-12	NULL	NULL
130	1.5-12	1-12	NULL
135	6-12	1-12	1-12
140	1.5-12	1-12	NULL
145	6-12	NULL	NULL
150	1.5-12	1-12	1-12
155	6-12	NULL	NULL
160	1.5-12	1-12	NULL
165	6-12	1-12	1-12
170	1.5-12	1-12	NULL
180	1.5-12	1-12	1-12

Figure 2 747 Low-Frequency Data Base Map

The Ohio State University ElectroScience Laboratory
Compact Range Experimental Data 1984
Scale factor = Elevation angle = 0 degrees

LOW FREQUENCY FORMATTED DATA BASE (GHz)

ASPECT (Deg)	POLARIZATION * HH *	* HV *	* VV *
0	1-12	1-12	1-12
10	1-12	NULL	1-12
15	1-12	1-12	1-12
20	1-12	1-12	1-12
25	6-12	NULL	6-12
30	1-12	1-12	1-6.3
35	6-12	NULL	6-12
40	1-12	1-12	1-12
45	1-12	1-12	1-12
50	1-12	1-12	1-12
55	6-12	NULL	6-12
60	1-12	1-12	1-12
65	6-12	NULL	6-12
70	1-12	1-12	1-12
75	1-12	1-12	1-12
80	1-12	1-12	1-12
85	6-12	NULL	6-12
90	1-12	1-12	1-12
95	6-12	NULL	6-12
100	1-12	1-12	1-12
105	1-12	1-12	1-12
110	1-12	1-12	1-12
115	6-12	NULL	6-12
120	1-12	1-12	1-12
125	6-12	NULL	6-12
130	1-12	1-12	1-12
135	1-12	1-12	1-12
140	1-12	1-12	1-12
145	6-12	NULL	6-12
150	1-12	1-12	1-12
155	6-12	NULL	6-12
160	1-12	1-12	1-12
165	1-12	1-12	1-12
170	1-12	1-12	1-12
175	6-12	NULL	6-12
180	1-12	1-12	1-12
270	6-12	NULL	1-12

Table 3 707 Low-Frequency Data Base Map

The Ohio State University ElectroScience Laboratory
Compact Range Experimental Data 1984
Scale factor = Elevation angle = 0 degrees

LOW FREQUENCY FORMATTED DATA BASE (GHz)

ASPECT (Deg)	POLARIZATION " HH "	" HV "	" VV "
0	1-12	1-12	1-12
10	1-12	1-12	1-12
15	1-12	1-12	1-12
20	1-12	1-12	1-12
30	1-12	1-12	1-12
40	1-12	1-12	1-12
45	1-12	1-12	1-12
50	1-12	1-12	1-12
60	1-12	1-12	1-12
70	1-12	1-12	1-12
75	1-12	1-12	1-12
80	1-12	1-12	1-12
90	1-12	1-12	1-12
100	1-12	1-12	1-12
105	1-12	1-12	1-12
110	1-12	1-12	1-12
120	1-12	NULL	1-12
130	1-12	NULL	1-12
135	1-12	NULL	1-12
140	1-12	1-12	1-12
150	1-12	1-12	1-12
160	1-12	1-12	1-12
165	1-12	1-12	1-12
170	1-12	1-12	1-12
180	1-12	1-12	1-12
270	1-12	1-12	1-12

Table 4 DC10 Low-Frequency Data Base Map

The Ohio State Univesity ElectroScience Laboratory
Compact Range Experimental Data 1984
Scale factor =   Elevation angle = 0 degrees

LOW FREQUENCY FORMATTED DATA BASE (GHz)

ASPECT (Deg)		POLARIZATION	
	* HH *	* HV *	* VV *
0	1-12	1-12	1-12
10	1-12	1-12	1-12
15	1-12	NULL	1-12
20	1-12	1-12	1-12
25	6-12	NULL	6-12
30	1-12	1-12	1-12
35	6-12	NULL	6-12
40	1-12	1-12	1-12
45	1-12	1-12	1-12
50	1-12	1-12	1-12
55	6-12	NULL	6-12
60	1-12	1-12	1-12
65	6-12	NULL	6-12
70	1-12	1-12	1-12
75	1-12	1-12	1-12
80	1-12	1-12	1-12
85	6-12	NULL	6-12
90	1-12	1-12	1-12
95	6-12	NULL	6-12
100	1-12	1-12	1-12
105	1-12	1-12	1-12
110	1-12	1-12	1-12
115	6-12	NULL	6-12
120	1-12	1-12	1-12
125	6-12	NULL	6-12
130	1-12	1-12	1-12
135	1-12	1-12	1-12
140	1-12	1-12	1-12
145	6-12	NULL	6-12
150	1-12	1-12	1-12
155	6-12	NULL	6-12
160	1-12	1-12	1-12
165	1-12	1-12	1-12
170	1-12	1-12	1-12
175	6-12	NULL	6-12
180	1-12	1-12	1-12

Table 5 Concord Low-Frequency Data Base Map

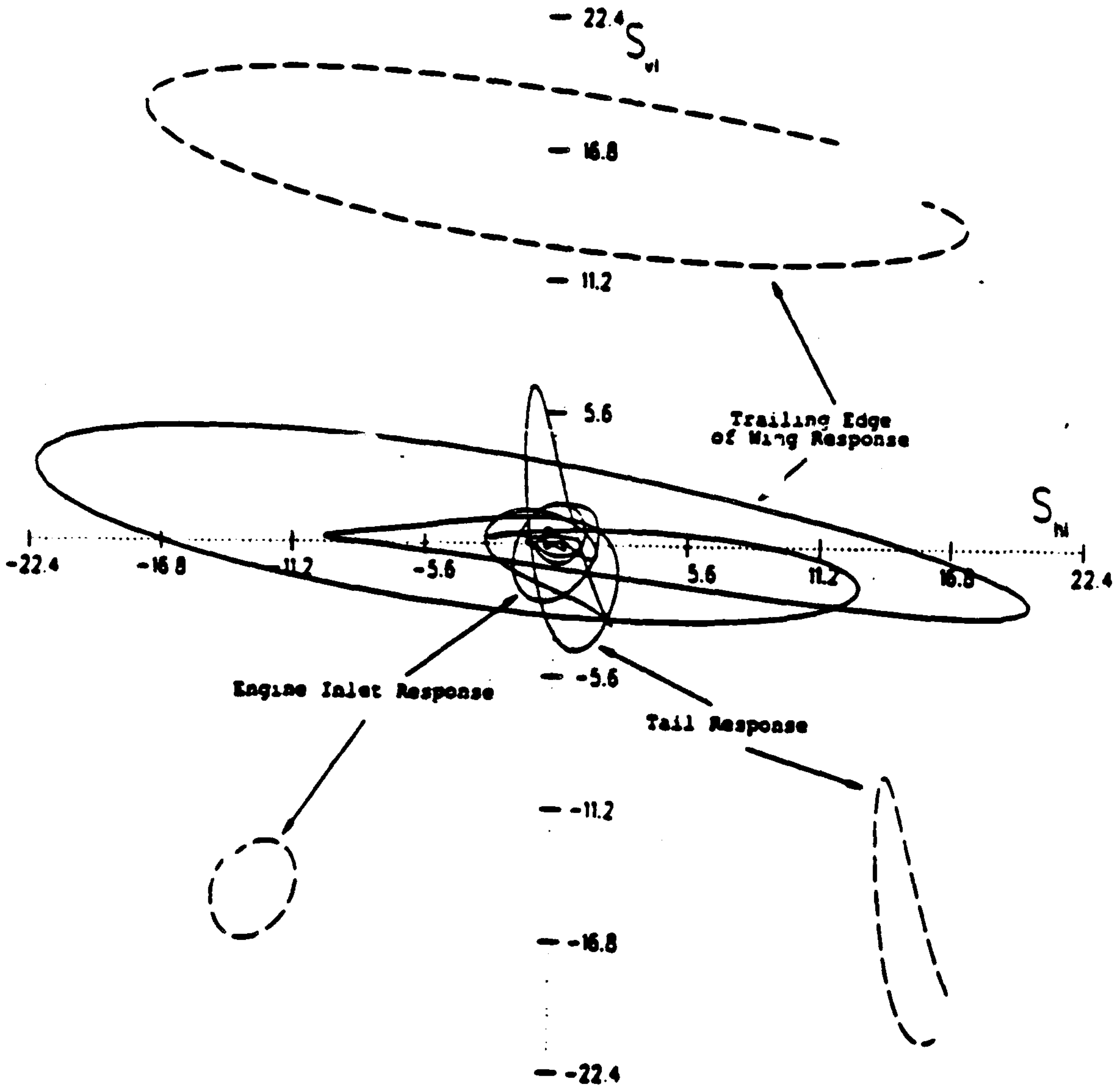


Figure 11: TPIR for the Concord at 0° viewed from the direction of propagation, showing E field locus.

ellipses. This, in turn, suggests that largest amplitude portions of the TPIR which correspond to the major scattering centers, can be represented by an elliptical parameterization.

The parameterization of the portions of the TPIR corresponding to the major scattering centers is accomplished by a best-fit ellipse approximation using a least-squares fitting algorithm. The set of features derived from this parameterization are the ellipticity ϵ, the tilt angle τ, and the amplitude A of the fitted ellipse. These three parameters describe object substructure geometries in a natural way. The overall size (cross-section) of the substructure determines the amplitude, the shape of the substructure is strongly related to the ellipticity, and the orientation determines the tilt angle.

18.4.2.3 TPIR Features for Commercial AC's

In *Table 6* we have the sets of features representing the engine inlet and tail derived from the TPIR's for the set of five commercial AC's which we have chosen to demonstrate our system. In this table, the amplitude A, the ellipticity ϵ and the tilt angle τ, are displayed along with the parameters t_s and t_e which are the times (in nanoseconds) marking the start and end of the corresponding response subsection[43]. The accurate values are shown and so are the intervals or ranges of values which account for any error in the measurements of the sensors. In other words, the ranges account for the possible inaccuracies in the observations.

AC's	t_s	t_e		A		ε		τ	Component
Concord	−0.065	0.125	A_1	1–5 (2.731)	ε_1	33–39 (36)	τ_1	48–68 (58)	Engine inlet
	0.940	1.135	A_2	5–9 (7.08)	ε_2	2–8 (5)	τ_2	94–114 (104)	Tail
DC–10	−0.272	−0.130	A_1	14–18 (15.908)	ε_1	9–15 (12)	τ_1	38–58 (48)	Engine inlet
	0.580	0.746	A_2	12–16 (13.622)	ε_2	6–12 (9)	τ_2	81–101 (91)	Tail
Boeing 707	−0.120	0.095	A_1	18–22 (20.265)	ε_1	1–7 (3)	τ_1	169–189 (179)	Engine inlet
	0.950	1.136	A_2	4–8 (6.405)	ε_2	6–12 (9)	τ_2	81–101 (91)	Tail
Boeing 727	−0.230	−0.108	A_1	1–5 (3.366)	ε_1	13–19 (16)	τ_1	157–177 (167)	Engine inlet
	0.360	0.477	A_2	4–8 (5.96)	ε_2	26–32 (29)	τ_2	3–23 (13)	Tail
Boeing 747	−0.300	−0.139	A_1	19–23 (21.24)	ε_1	26–32 (29)	τ_1	49–69 (59)	Engine inlet
	1.320	1.471	A_2	11–15 (12.59)	ε_2	2–8 (5)	τ_2	89–109 (99)	Tail

Note: The figures in the brackets correspond to the accurate measurements and the ones like 4–8 correspond to the ranges or the observation interval. A,ε and τ correspond to the amplitude, ellipticity and the tilt angle of the ellipse.

Table 6 <u>SET OF FEATURES REPRESENTING ELLIPTICITY DATA</u>

18.4.3 SAMPLE IMPLEMENTATION

In *Figure 5*, the KSs marked with asterisks are the ones used for the sample implementation. The user supplies the data to our system instead of the situation data base. In a real life situation, an input program would extract it directly from the situation data base. The present simulation[2] performs classification of an AC, after identifying it by its features, into disjoint sets (object classes) comprising of the five commercial ACs (Boeing 747, Boeing 707, DC10, Concord and Boeing 727).

The two KSs in our system are ASPOL and ELLIPT the theoretical basis of which has been briefly discussed above. For more details, the interested reader is referred to the references presented in the above discussion. Each KS is implemented as a condition-action pair. Both of the KSs have been developed to perform a variety of functions and are capable of accounting for inaccurate or insufficient data. KSs communicate with each other through the blackboard, a global database, which records the hypotheses generated by KSs, combines them and has a confidence KS built into it. If either ASPOL or ELLIPT is not able to post its hypothesis then the PS activity continues on the basis of the other KS only and the system warns the user that the object identification theory might be unreliable and should not be pursued any further.

2 refer to the appendices A and B for the *Lisp program code* and *sample runs* respectively.

18.4.4 THE PROBABILITY BASIS

Our system is employed in domains where conclusions are rarely certain. Thus, we have to build some sort of certainty–computing procedure on top of the basic antecedent–consequent apparatus. Our certainty/confidence computation procedure associates a number between 0 and 1 with each fact. This number, called a *certainty factor*, is intended to reflect how much confidence we have in the fact or how much certain the fact is, with 0 indicating that a fact is definitely false and 1 indicating that a fact is definitely true.

18.4.4.1. The blackboard

In the blackboard, a fact's certainty is to be determined when the consequents of several antecedent-consequent rules argue for it, requiring the computation of a *multiply argued certainty*[44]. To calculate multiply argued certainties, certainty ra-

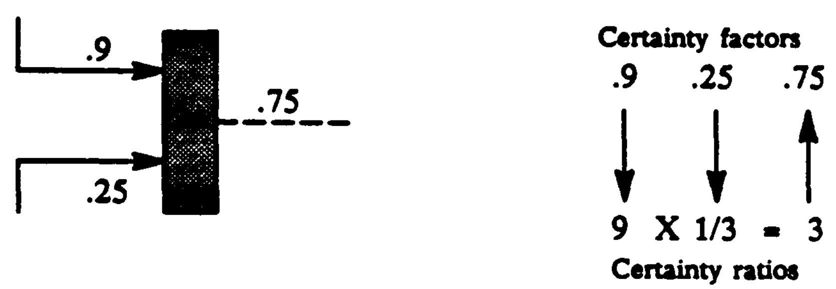


Figure 12 THE INFERENCE NET PROCEDURE FOR COMBINING CERTAINTY FACTORS

tios are used. Certainty factor, c, and a certainty ratio, r, are related as follows:

$$r = \frac{c}{1-c} \qquad c = \frac{r}{r+1}$$

The certainty of a multiply argued consequent is determined by transforming to certainty ratios, multiplying, and transforming back to certainty factors. This is shown in the *Figure 12.*

After certainties are transformed into certainty ratios, the certainty ratio of a multiply argued consequent is given by the following formula:

$$r_0 \times \frac{r_1}{r_0} \times \ldots\ldots \times \frac{r_n}{r_0}$$

where r_0 is the certainty ratio corresponding to the a priori certainty of the consequent, and the r_i are the certainty ratios corresponding to the certainties read from the input–output functions of the contributing rules. Note that the formula reduces to the product of certainty ratios in the special case when the a priori certainty ratio is 1. This corresponds to the case when the a priori certainty of the consequent is .5. In this special situation, the prior evidence does not indicate whether the hypothesis is true or false.Transforming certainties into certainty ratios to compute the certainty of multiply argued consequents is a powerful technique for knowledge based systems. For a detailed discussion of this subjective Bayesian inference method, the reader is referred to Duda et. al.[45].

18.4.4.2 The ELLIPT knowledge source

ELLIPT knowledge source shown in *Figure 13* first checks against the entries of *Table 6* for the available ranges for the identification of the object as belonging to one of the classes of ACs. It then uses heuristics to assign the confidence values to the remaining ACs in the decreasing order of priority based on the "closeness" which they exhibit to the identified AC, see *Table 7*. The degree of closeness of a particular AC to the identified AC is the amount of features that they have in common. In other words, what is the confidence in the hypothesis that it "could have been" some other AC if it was not the one that has been identified.

The hypothesis posted by the ELLIPT KS is a list comprising of the confidences which it assigns to each of the five ACs. The confidence in the identified AC being equal to the overall confidence in the KS itself, which is assigned by the operator depending on the kind of measurement (derived measurement in the present case), the confidence in the sensor which is being modeled by the KS and various other factors. In *Table 7* weights assigned to all the entries of the table are equal.

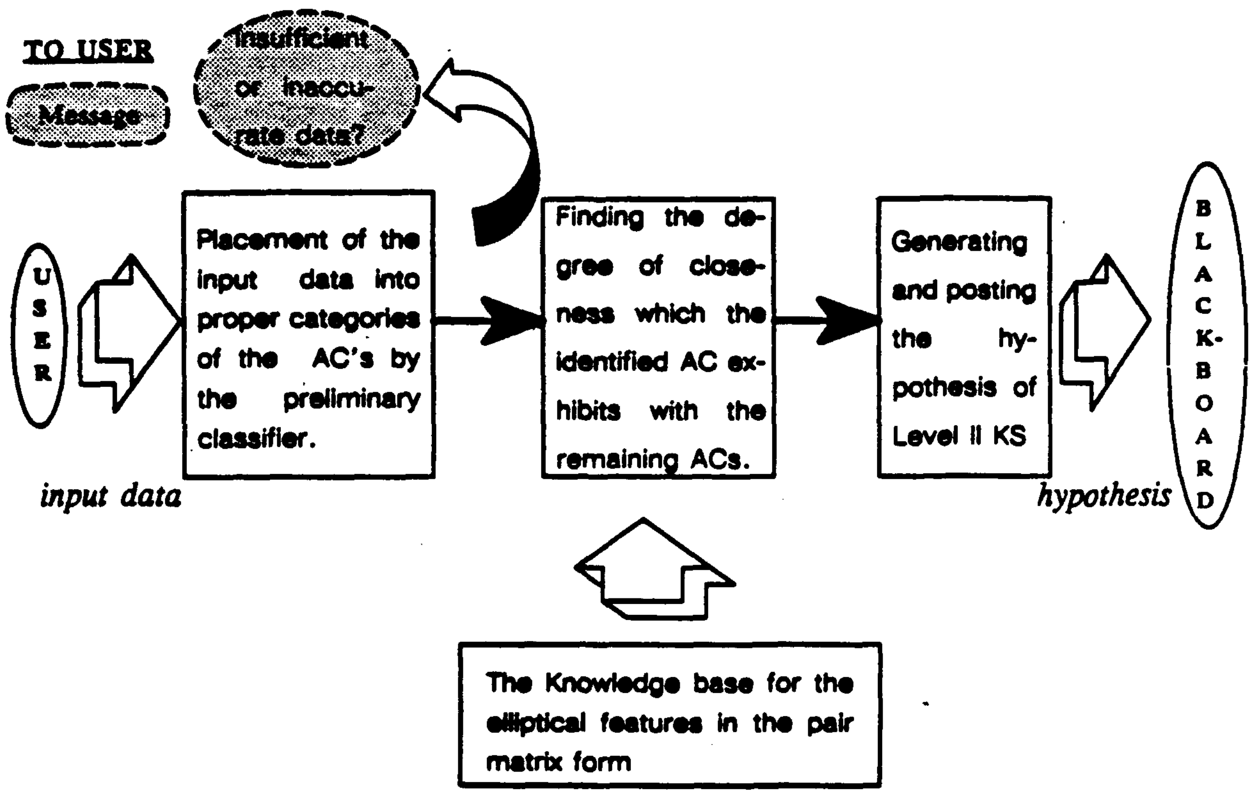


Figure 13 THE ELLIPT KNOWLEDGE SOURCE IN OUR SYSTEM

C	C OR 72	C OR 74	C OR 70	C OR DC
A_1	1 - 5	X	X	X
A_2	5 - 8	X	5 - 8	X
ϵ_1	X	X	X	X
ϵ_2	X	2 - 8	6 - 8	6 - 8
τ_1	X	48 - 68	X	48 - 58
τ_2	X	94 - 101	94 - 101	94 - 101

DC	DC OR C	DC OR 72	DC OR 74	DC OR 70
A_1	X	X	X	X
A_2	X	X	12 - 15	X
ϵ_1	X	13 - 15	X	X
ϵ_2	6 - 8	X	6 - 8	6 - 12
τ_1	48 - 58	X	X	X
τ_2	94 - 101	X	89 - 101	81 - 101

747	74 OR C	74 OR 72	74 OR 70	74 OR DC
A_1	X	X	19 - 22	X
A_2	X	X	X	12 - 15
ϵ_1	X	X	X	X
ϵ_2	2 - 8	X	6 - 8	6 - 8
τ_1	48 - 68	X	X	X
τ_2	94 - 101	X	89 - 101	89 - 101

727	72 OR C	72 OR 74	72 OR 70	72 OR DC
A_1	1 - 5	X	X	X
A_2	5 - 8	X	5 - 8	X
ϵ_1	X	X	X	13 - 15
ϵ_2	X	X	X	X
τ_1	X	X	169 - 177	X
τ_2	X	X	X	X

707	70 OR C	70 OR 74	70 OR 72	70 OR DC
A_1	X	19 - 22	X	X
A_2	5 - 8	X	5 - 8	X
ϵ_1	X	X	X	X
ϵ_2	6 - 8	6 - 8	X	6 - 12
τ_1	X	X	169 - 177	X
τ_2	94 - 101	89 - 101	X	81 - 101

Table 7 THE KNOWLEDGE BASE FOR ELLIPTICAL FEATURES IN THE PAIR MATRIX FORM

NOTATION: The entries marked X stand for the features which are not common amongst the pair of ACs. The values stand for the feature overlap, and are also indicative of the range of error allowable for the corresponding sensor. C, DC, 707 etc. correspond to Concord, DC10, Boeing 707 ACs respectively. The features A_1, A_2 etc. have already been explained in the table of elliptic features. Each of them carries equal weight and they are equally determinable.

18.4.4.3 The ASPOL knowledge source

The ASPOL knowledge source models the system's aspect angle and polarization sensors. It receives/accepts the data from the user as a list with the aspect angle followed by the HH, HV and VV polarizations. It checks for each of the ACs in the following sequence: Boeing-747, DC10, Concord, Boeing-727 and Boeing-707. It interacts with the user/system operator for getting more data, thus, facilitating the generation of a hypothesis if it is so required. It also has provisions for checking if the data is out of bounds at any stage and asks the user to re-enter it. In other words, it delays communication with the blackboard until it is able to generate a satisfactory hypothesis. The user/ system operator has the option of specifying that he does not have sufficient data in which case the equivalent of no hypothesis is posted on the blackboard and the problem solving activity continues by the hypotheses posted by remaining KSs. As we can see, in a real life situation, a key feature of the ASPOL KS would be that it would be able to request more data from the data grouping unit and hence the sensor, if it suspects an object but has less than the information needed to generate and post a hypothesis. The confidence values it assigns to the ACs is solely dependent on the values suggested by the system operator thus taking into account the effect of experience and the human reasoning.

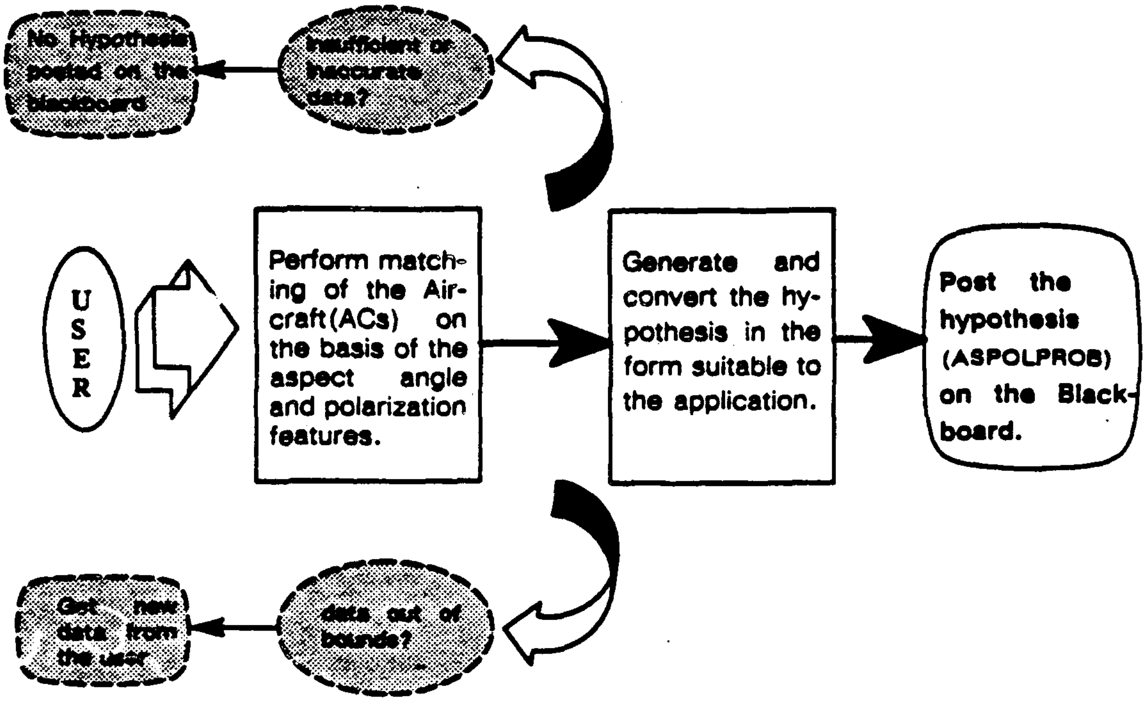


Figure 14 <u>THE ASPOL KNOWLEDGE SOURCE IN OUR SYSTEM</u>

18.4.5 SUMMARY

To demonstrate the framework presented above, the data base which we utilize in our implementation is a subset of the expert reasoning mentioned in the earlier chapters. It is in the form of table entries for each kind of sensor. Each sensor is being modeled by a KS. In real life situation, these entries would be extracted from the situation data base, replacing the user who is currently responsible for supplying the data to the system.The data base consists of calibrated complex (coherent) monostatic radar returns measured at various azimuth angles, frequencies, and polarizations, at an elevation and roll angle of 0 degree and the ellipticity data. The two KSs, ASPOL and ELLIPT in our system stand for the aspect angle, polarization information (direct measurements) and ellipticity information (derived measurements).

18.5 SUMMARY & POSSIBLE EXTENSIONS

18.5.1 SUMMARY AND DISCUSSION

Our approach utilizes the blackboard for information management and hypotheses combination. The blackboard is used by knowledge sources (KSs) for sharing information and posting their hypotheses on, just as experts sitting around a round table would do. A situation data base is characterized by experimental data available from the three levels of expert reasoning. These are *direct measurements* (polarization, signatures & effects etc.), *derived and behavioral measurements* (temporal, act based, ellipticity and classification based on frequencies etc.) and *contextual interpretation* (contextual threat, priority zone assignment, pattern for attack intention and fact based information from military intelligence). These KSs generate intermediate hypotheses and all these hypotheses appear at different levels of abstraction on the blackboard. The posted hypothesis is refined and confidence level of the best explanation is checked to determine if it meets the requirements for being an object identification/classification theory.

It should be pointed out that such considerations as the enhancement of the signal with respect to noise, or the suppression of other forms of background interference sources e.g., what is commonly referred to as 'clutter', were not discussed since it fell outside the scope of this report.

18.5.2 POSSIBLE EXTENSIONS

The directions of possible extensions are many, however we shall discuss only the ones which seem to hold the most promise. Addition of the contextual interpretation knowledge sources to take into account "human like" decision making could be the first avenue that can be tried. The two different kinds of informations for the contextual interpretation knowledge sources are described below. These could be entered in the form of simple question answer sessions of the system and the user/system operator/battle commander. An important thing to note is that these do not affect the identification task or the classification performed. Their effect is limited to adding weights or confidence to the object identification theory. However, it *could* have its effect on the decision taken by advising or guiding the system operator of the context of the situation and its implications. Application of Object Oriented Programming techniques to the identification and classification task in multiple sensor data fusion problems is another avenue which could be explored. These are discussed in the following sections.

18.5.2.1 Contextual Interpretation

The contextual interpretation has been discussed in the expert reasoning in the earlier chapters. The two types of contextual knowledges which we could utilize are the priority zone information and pattern for attack intention. These are the topics of discussion which follows.

Priority zones

Priority zones [3] are regions of the radar's observation volume having the likelihood of serious threats appearing in them and of the corresponding degree of desire to maintain high quality detection and tracking. It is presently assumed that the operator will assign these priorities, although automated situation assessment and priority assignment is being considered. The five priority ratings to be used are high threat, medium threat, low threat, friendly, and unoccupied. Three situations can be considered in priority assignment : protection of the radar, protection of the forward edge of the battle area (FEBA), and protection of a point behind FEBA. The present intention could be to deal only with situations that can be recognized from a single scan of the radar, so zone definitions are restricted to simple range and azimuth limits as in *Figure 15*.

Pattern for Attack Intention

Ben–Bassat and Freedy [46] discuss pattern for attack intention, which can be used as another form of Contextual Interpretation KS. The *Table 8* discusses the probability basis of the class: attack intention.

18.5.2.3... Object Oriented Programming

Another possible extension could be making use of the Object Oriented Programming techniques using the *flavor* macros in Common LISP. The *Figure 16* shows the organization of a system making use of flavor macros and object oriented programming. Representation of the objects (ACs for our case) could be done using the defflavor form, which defines a flavor that represents ACs. As

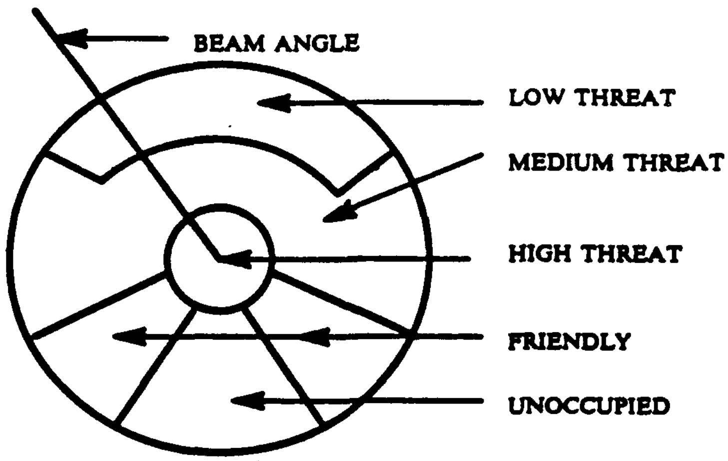


Figure 15 <u>ZONE ASSIGNMENTS FOR PROTECTION OF THE RADAR, FOR THE ZONE PRIORITIZATION</u>

Note: one could similarly define the zone assignments for the protection of FEBA under zone prioritization.

Table 8

A Pattern for Attack Intention:

Class: Attack Intention

Features	p	-p
• massing of mechanized elements	0.8	0.3
• extensive artillery preparation	0.8	0.4
• artillery position concentrated	0.8	0.2
• concentration of mass toward either or both flanks	0.7	0.3
• location of enemy troops in forward assembly area	0.8	0.3
• location of supply and evacuation installations well forward	0.7	0.3
• increased air reconnaissance	0.8	0.4
• movement of additional troops toward the front	0.8	0.4

shown, each real world object is represented by a Lisp object and the inherent structure of objects is called flavor. The output of the *generic functions*, unlike normal functions, is different for objects of different flavors for the same input. *Methods* is a piece of code which implements the Generic functions on the lisp objects. The AC flavor is a framework, and we could fit many ACs into that framework. We represent each real-life AC as an *instance* of the AC flavor. Each instance would store information about one particular AC in its instance variables. To create or simulate instances we could use, make-instance. Querying the instance for its values would also be possible because of a function that was automatically generated. New operations (generic functions) for instances of the AC flavor could be defined using defmethod.

As it is seen from the above discussion, object oriented technique, which provides a means of configuring everything in a system around objects, could be investigated more for dealing with the object classification problems.

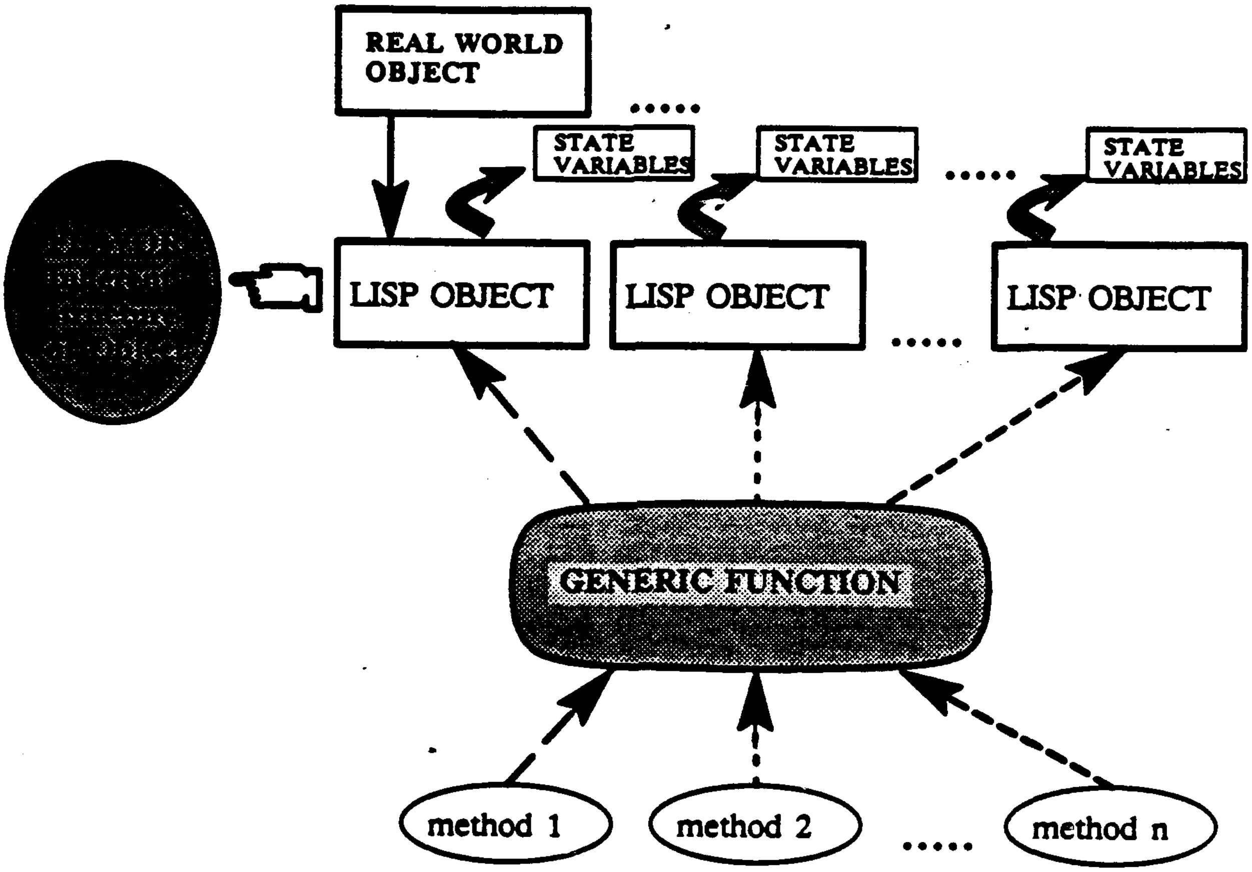


Figure 16 POSSIBLE USE OF OBJECT ORIENTED PROGRAMMING FOR OUR CASE.

APPENDIX

A

COMMON LISP PROGRAM CODES

A-1

THE ASPOL AND ELLIPT KNOWLEDGE SOURCES

```
;;; ************************************************************************
;;; This is the LEVEL 1 KS. Name ASPOL Knowledge source. A few things to

;;; be noted here, This is an interactive program. The user

;;; shall be replaced by another piece of code which

;;; does the data input directly from the SITUATION

;;; DATA BASE in the real life situation.

;;; SYNTAX COMMON LISP

;;; Created By Digvijay Sikka for SUDAI System.

;;; Created Sept. 20, 1988

;;; Modified Nov. 3, 1988: Dec. 23,1988.
;;; ************************************************************************

;;; This function begins by checking if the object is a Boeing-747,

;;; It calls confirm, confirm2 and checks if the data is out of bounds,

;;; in which case it prompts the user to enter a new list.

(defvar *a* nil)
(defvar *b* nil)
(defvar *c* nil)
(defvar *r* nil)
(defvar *d* nil)
(defvar *e* nil)
(defvar *ainp* nil)
(defvar *ainp1* nil)

(defun check-AC (*list1*)
 (print "
********* Level I KS: ASPOL.************

It is possible that data out of bounds might have been given
at this stage, but it is not of significant interest to me since no
```

```
decision about the proof of identity of the object has yet been taken.
However very soon the identity of the Object shall be established.")
 (cond
  ((equalp (cadr *list1*) '112)
   (dc10 ))
  (t
   (confirm *list1*))))

(defun confirm (*list1*)
 (cond
  ((or (equalp (cdr *list1*) '(612 null 612))
       (equalp (cdr *list1*) '(612 null 112)))
  (dc10 ))
  (t
   (confirm2 *list1*))))

(defun confirm2 (*list1*)
 (cond
  ((or (equalp (cdr *list1*) '(1.512 112 null))
       (equalp (cdr *list1*) '(612 112 112))
       (equalp (cdr *list1*) '(1.512 112 112))
       (equalp (cdr *list1*) '(612 null null)))
  (print "
**************************
**Object is a Boeing-747**
**************************")
  (print "These are the confidence values
of the AC's in the following order (Concorde Boeing727 Boeing707 DC10 Boeing747):")
  (list74))
  (t
   (print "

ERROR, possibility of being any other AC is low, and data out of bounds
 for Boeing 747, give another value")
   (check-AC (accept '(list))))))
```

```
(defun list74 ()
  (setq *ASPOLPROB* (list 0.2 0.2 0.2 0.3 0.9))
  (print *ASPOLPROB*))


;;; This function checks for the possibility of the Aircraft being

;;; anything other than Boeing-747 since it has already confirmed that

;;; it is not Boeing-747. It prompts the user to input values for aspect

;;; angles 120, 130, 135.

(defun dc10 ()
  (print "
************************************
**The Object is not a Boeing-747**
************************************,

**Please enter the Polarization
        Values (120 hh hv vv) for Aspect angle 120:")
  (setq *a* (read))
  (print "Now enter those for Aspect angle 130 (130 hh hv vv):")
  (setq *b* (read))
  (print "Now enter those for Aspect angle 135 (135 hh hv vv):")
  (setq *c* (read))
  (if (and (equalp (car *a*) '120)
           (equalp (car *b*) '130)
            (equalp (car *c*) '135)) (confirmdc10 *a* *b* *c*)  (print "

There appears to be some inconsistency with the Aspect
angle values, I am going over it again:")
   (dc10)))

;;; This function checks if the object is a DC-10, if it encounters data out of

;;; bounds it notifies the user and expects new values. It also calls confirmconc

;;; to check for the object being one of Boeing-707,727 or Concorde.
```

```
(defun confirmdc10 (*a* *b* *c*)
  (cond
   ((and (equalp (cdr *a*) '(112 null 112))
         (equalp (cdr *b*) '(112 null 112))
         (equalp (cdr *c*) '(112 null 112)))
   (print "
*************************
**The Object is a DC-10**
*************************

These are the confidence values of the ACs, their order is,
 (Concord Boeing727 Boeing707 DC10 Boeing747): ")
    (setq *ASPOLPROB* (list 0.2 0.2 0.2 0.9 0.3))
   (print *ASPOLPROB*))
   (t
    (if (and (equalp (cdr *a*) '(112 112 112))
             (equalp (cdr *b*) '(112 112 112))
              (equalp (cdr *c*) '(112 112 112))) (confirmconc) (print "


ERROR, Data out of Bounds

MESSAGE:
This Knowledge source would not be able to generate and post a

hypothesis based on the data you have supplied. If you do not have

sufficient data please reply a YES to the following question (and the

identification and classification shall proceed only on the basis of

the remaining KS's) however, if you want to reenter data correctly,

after answering a NO to the question, please enter it again. ") (modaspol)))))

(defun modaspol ()
  (print "

Message:
Do you have insufficient or inaccurate data?")
```

```
 (setq *ainp* (read))
 (cond ((eq *ainp* 'no)
        (dc10))
       (t
        (setq *ASPOLPROB* (list 0.01 0.01 0.01 0.01 0.01)))))

;;; This function first calls ask-YorN to ask the user if he has

;;; Data for the Aspect angles 10 and 15, if he doesn't then the

;;; the Program returns the message "Insufficient information" and

;;; outputs partial list, because it needs other measures for coming

;;; to a decision.

(defun confirmconc ()
 (print "
** The Object is not a DC-10 OR BOEING-747 **
***But I shall try checking if it is one of BOEING-707, BOEING-727 and CONCORDE***")
 (ask-YorN)
 (cond ((eq *r* 'yes)
        (conc ))
       (t
        (setq *ASPOLPROB* (list 0.01 0.01 0.01 0.01 0.01)))))

(defun ask-YorN ()
 (print "

MESSAGE,
Is Polarization data available for aspect angles 10 and 15?
If any one or none of them is available I have insufficient data. The
identificaiion and classification shall then proceed on the basis of
other KS's. Answer a NO for that case. Please answer YES if polarization
values for both of them are available:")
 (setq *r* (read)))

;;; The user is prompted to enter values of polarization for the

;;; aspect angles 10 and 15. It calls concorde if the data is not out of
```

```
;;; bounds in which case it calls itself.

(defun conc ()
  (print "

**This is to check if it is a Boeing-707 or Boeing-727
or Concorde, Please enter the values of polarization for Aspect
                angle 15, e.g (15 hh hv vv):")
  (setq *d* (read))
  (print "Now enter those for Aspect 10, e.g (10 hh hv vv):")
  (setq *e* (read))
  (cond
   ((and (equalp (car *d*) '15)
         (equalp (car *e*) '10))
    (concorde *d*))
   (t
    (print "

ERROR,
Aspect angle data out of bounds, Please give it again:")
    (conc))))

(defun concorde (*d*)
  (cond ((equalp (cdr *d*) '(112 112 112))
         (print "

MESSAGE,
** The Object is not a DC-10 or BOEING-747 or CONCORDE **

Checking if it is either BOEING-727 OR 707..............................

")
         (confirm727 *e*))
        (t
         (if (and (equalp (caddr *d*) 'null)
                  (equalp (cdr *e*) '(112 112 112))) (listconcd)
           (print "
```

```
ERROR, Data out of Bounds

MESSAGE:
This Knowledge source would not be able to generate and post a

hypothesis based on the data you have supplied. If you do not have

sufficient data please reply a YES to the following question (and the

identification and classification shall proceed only on the basis of

the remaining KS's) however, if you want to reenter data correctly,

after answering a NO to the question, please enter it again. ") (modaspoll)))))

(defun modaspoll ()
  (print "

Message:
Do you have insufficient or inaccurate data?")
  (setq *ainp1* (read))
  (cond ((eq *ainp1* 'no)
         (conc))
        (t
         (setq *ASPOLPROB* (list 0.01 0.01 0.01 0.01 0.01)))))

(defun listconcd ()
  (print "
******************************
** The Object is a CONCORDE **
******************************

These are the Confidence values of the AC's in the following order (Concord
Boeing727 Boeing707 DC10 Boeing 747 ):")
  (setq *ASPOLPROB* (list 0.9 0.3 0.3 0.2 0.1))
  (print *ASPOLPROB*))

;;; This function checks for if the object is a Boeing-727 or Boeing-707

;;; it also prompts the user if the values given are not appropriate.
```

```
;;; the user migh  wish to quit by hitting Abort at the Keyboard.

(defun confirm727 (*e*)
  (cond ((equalp (cdr *e*) '(112 112 112))
        (print "
********************************
** The Object is a BOEING-727 **
********************************") (print "

These are the Confidence factors of the
AC's, their order being (Concord Boeing727 Boeing707 DC10 Boeing747):") (list727))
       (t
        (if (equalp (cdr *e*) '(112 null 112)) (list707)
       (print "

ERROR,
The values given are not appropriate, please check them
and enter them again if you wish to continue at this stage,
or else hit Abort, to start all over again." )
        (conc)))))

(defun list707 ()
  (print "
********************************
** The Object is a BOEING-707 **
********************************

The confidence factors of the ACs are as following, their order being
 (Concord Boeing727 Boeing707 DC10 Boeing747):")
  (setq *ASPOLPROB* (list 0.4 0.6 0.9 0.1 0.1))
  (print *ASPOLPROB*))

(defun list727 ()
  (setq *ASPOLPROB* (list 0.4 0.9 0.6 0.1 0.1))
  (print *ASPOLPROB*))

;;;**************** End Of File for IV Level CheckAC *******************
```

```lisp
;;; -*- Mode: LISP -*-
;;; ******************************************************************
;;; This is LEVEL 2 KS. Name: ELLIPT Knowledge Source (Derived measurements).
;;; The ellipt function checks the input given by the user to see if it belongs to the
;;; range of any of the AC's. If it  does not then it exits.If a user doesnot seem
;;; to have sufficient data then it doesnot post any hypothesis on the blackboard
;;; and the decision making proceeds without Ellipt ks.
;;; Created November 30 '88 by Digvijay Sikka.
;;; Last modified Jan 08 '89.
;;; ******************************************************************

(defvar *A1* nil)
(defvar *A2* nil)
(defvar *e1* nil)
(defvar *e2* nil)
(defvar *t1* nil)
(defvar *t2* nil)
(defvar *oi* nil)

(defun ellipt (*list2* *list3*)
  (setq *A1* (caddr *list2*))
  (setq *A2* (caddr *list3*))
  (setq *e1* (cadddr *list2*))
  (setq *e2* (cadddr *list3*))
  (setq *t1* (fifth *list2*))
  (setq *t2* (fifth *list3*))
  (ELLCONC))

(defun ELLCONC ()
  (if (and (<= 1 *A1* 5)
           (<= 33 *e1* 39)
           (<= 48 *t1* 68)
           (<= 5 *A2* 9)
           (<= 2 *e2* 8)
           (<= 94 *t2* 114)) (ELLCHKC) (ELLDC10)))

(defun ELLDC10 ()
  (if (and (<= 14 *A1* 18)
           (<= 9 *e1* 15)
           (<= 38 *t1* 58)
```

```
          (<= 12 *A2* 16)
          (<= 6 *e2* 12)
          (<= 81 *t2* 101)) (ELLCHKDC) (ELLB707)))

(defun ELLB707 ()
  (if (and (<= 18 *A1* 22)
          (<= 1 *e1* 7)
          (<= 169 *t1* 189)
          (<= 4 *A2* 8)
          (<= 6 *e2* 12)
          (<= 81 *t2* 101)) (ELLCHK70) (ELLB727)))

(defun ELLB727 ()
  (if (and (<= 1 *A1* 5)
          (<= 13 *e1* 19)
          (<= 157 *t1* 177)
          (<= 4 *A2* 8)
          (<= 26 *e2* 32)
          (<= 3 *t2* 23)) (ELLCHK72) (ELLB747)))

(defun ELLB747 ()
  (if (and (<= 19 *A1* 23)
          (<= 26 *e1* 32)
          (<= 49 *t1* 69)
          (<= 11 *A2* 15)
          (<= 2 *e2* 8)
          (<= 89 *t2* 109)) (ELLCHK74) (messge) (modellipt *list2* *list3*)))

(defun messge ()
  (print "

*****************************************************************

Ellipt Knowledge Source has not been able to generate and post a HYPOTHESIS

based on the data you have supplied. If you do not have the data please reply

a YES to the following question (and the identification and classification

shall proceed only on the basis of the existing HYPOTHESIS posted by ASPOL KS)

however, if you want to reenter data correctly, after answering
```

```
a NO to the question, please enter it again.
**********************************************************************"))

(defun modellipt (*list2* *list3*)
  (print "

 MESSAGE,
 Do you have insufficient or inaccurate data?")
  (setq *oi* (read))
  (cond ((eq *oi* 'no)
          (nuinput))
        (t
          (setq *ELLPROB* (list .01 .01 0.01 0.01 0.01)))))

(defun nuinput ()
  (print "

Enter the data for ENGINE INLET:")
  (setq *list2* (read))
  (print "

Now enter the data for  TAIL:")
  (setq *list3* (read))
  (ellipt *list2* *list3*))

(defun ELLCHKC ()
  (setq *ELLPROB* (list (cprobconc) (cprob727) (cprob707) (cprobdc10) (cprob747)))
  (print "

---------------------------------------------------------------------------
The confidence in the  CONCORDE  is the highest and is: 0.7. The confidence in each of
the remaining AC's is the following, their order being
 (Concorde Boeing727 Boeing707 DC10 and Boeing747):

")
  (print *ELLPROB*)
  (print "
------------------------------------------------------------------------------"))

(defun ELLCHKDC ()
  (setq *ELLPROB* (list (cprobdc10) (dcprob727) (dcprob707) (dcprobdc10)
  (dcprob747)))
  (print "
```

```
--------------------------------------------------------------------------------
The confidence in the  DC10  is the highest and is: 0.7. The confidence in each of the
remaining AC's is the following, their order being  (Concorde Boeing727 Boeing707 DC10
and Boeing747):

")
  (print *ELLPROB*)
  (print "
--------------------------------------------------------------------------------"))

(defun ELLCHK74 ()
  (setq *ELLPROB* (list (cprob747) (72prob747) (74prob707) (dcprob747) (74prob747)))
  (print "

--------------------------------------------------------------------------------
The confidence in the  BOEING 747 is the highest and is: 0.7. The confidence in
each of the remaining AC's is the following, their order being
 (Concorde Boeing727 Boeing707 DC10 and Boeing747):

")
  (print *ELLPROB*)
  (print "
-------------------------------------------------------------------------------- "))

(defun ELLCHK70 ()
  (setq *ELLPROB* (list (cprob707) (72prob707) (70prob707) (dcprob707) (74prob707)))
  (print "

--------------------------------------------------------------------------------
The confidence in the  BOEING 707 is the highest and is: 0.7. The confidence in
each of the remaining AC's is the following, their order being
 (Concorde Boeing727 Boeing707 DC10 and Boeing747):

")
  (print *ELLPROB*)
  (print "
-------------------------------------------------------------------------------- "))

(defun ELLCHK72 ()
  (setq *ELLPROB* (list (cprob727) (72prob727) (72prob707) (dcprob727) (72prob747)))
  (print "
```

The confidence in the *BOEING 727* is the highest and is: 0.7. The confidence in each of the remaining AC's is the following, their order being
(Concorde Boeing727 Boeing707 DC10 and Boeing747):

```
")
  (print "ELLPROB")
  (print "
---------------------------------------------------------------------- "))

(defun cprcbconc ()
  0.7)

(defun dcprobdc10 ()
  0.7)

(defun 72prob727 ()
  0.7)

(defun 74prob747 ()
  0.7)

(defun 70prob707 ()
  0.7)

(defun cprob727 ()
  (float (+ (genprobA11) (genprobA21))))

(defun cprob707 ()
  (float (+ (genprobA21) (genprobe22) (genprobt21))))

(defun cprob747 ()
  (float (+ (genprobe21) (genprobt11) (genprobt21))))

(defun cprobdc10 ()
  (float (+ (genprobe22) (genprobt12) (genprobt21))))

(defun dcprob727 ()
  (float (genprobe1)))

(defun dcprob747 ()
  (float (+ (genprobA22) (genprobe22) (genprobt22))))

(defun dcprob707 ()
  (float (+ (genprobe23) (genprobt23))))
```

```
(defun 74prob707 ()
  (float (+ (genprobA12) (genprobe22) (genprobt22))))

(defun 72prob707 ()
  (float (+ (genprobA21) (genprobt13))))

(defun 72prob747 ()
  0.01)

(defun genprobt13 ()
  (cond ((<= 169 *t1* 177) .116)
        (t
         .01)))

(defun genprobe1 ()
  (cond ((<= 13 *e1* 15) .116)
        (t
         .01)))

(defun genprobA11 ()
  (cond ((<= 1 *A1* 5) .116)
        (t
         .01)))

(defun genprobA21 ()
  (cond ((<= 5 *A2* 8) .116)
        (t
         .01)))

(defun genprobe21 ()
  (cond ((<= 2 *e2* 8) .116)
        (t
         .01)))

(defun genprobe22 ()
  (cond ((<= 6 *e2* 8) .116)
        (t
         .01)))

(defun genprobt11 ()
  (cond ((<= 48 *t1* 68) .116)
        (t
         .01)))
```

```
(defun genprobt12 ()
  (cond ((<= 48 *t1* 58) .116)
        (t
         .01)))

(defun genprobt21 ()
  (cond ((<= 94 *t2* 101) .116)
        (t
         .01)))

(defun genprobA22 ()
  (cond ((<= 12 *A2* 15) .116)
        (t
         .01)))

(defun genprobt22 ()
  (cond ((<= 89 *t2* 101) .116)
        (t
         .01)))

(defun genprobe23 ()
  (cond ((<= 6 *e2* 12) .116)
        (t
         .01)))

(defun genprobt23 ()
  (cond ((<= 81 *t2* 101) .116)
        (t
         .01)))

(defun genprobA12 ()
  (cond ((<= 19 *A2* 22) .116)
        (t
         .01)))
;;;*********************End of file for ELLIPT KS.***************************
```

APPENDIX 16.2

THE BLACKBOARD

```
;;; -*- Mode: LISP -*-
;;; Syntax: Common Lisp. Base: 10
;;; ************************************************************************
;;; This is the premilinary Blackboard written primarily for
;;; combining the ASPOL and ELLIPT KS's hypothesis, along with their
;;; confidence factors.It has a built in confidence check which prompts
;;; the user that the object identification theory might be unreliable
;;; and should not be pursued further if the confidence of the output
;;; is dangerously low.
;;; Syntax Common Lisp
;;; By Digvijay I Sikka for the Distributed Artificial Intelligence
;;; System.
;;; created Dec 17, '88.
;;; last modified Jan 7, '88.
;;; ************************************************************************

(defvar *ASPOLPROB* nil)
(defvar *ELLPROB* nil)
(defvar *firstcom* nil)
(defvar *secndcom* nil)
(defvar *thirdcom* nil)
(defvar *forthcom* nil)
(defvar *fifthcom* nil)
(defvar *list1* nil)
(defvar *list2* nil)
(defvar *list3* nil)
(defvar *confidence* nil)
(defvar *prd1* nil)
(defvar *prd2* nil)
(defvar *prd3* nil)
(defvar *prd4* nil)
(defvar *prd5* nil)
(defvar *userconf* nil)
```

```
(defun presentation ()
 (print "

**********************************************************************
**********************************************************************
THIS IS THE DAI SYSTEM FOR THE IDENTIFICATION AND CLASSIFICATION
                              OF AIRCRAFTS (ACs).
The ACs which we shall be classifying belong to one of the following five categories,
Concorde, Boeing 747, Boeing 727, Boeing 707 and DC10.

**********************************************************************
**********************************************************************
You as a User are simulating the situation data base where the sensors shall feed in the
data, and a Program shall extract it in real life situation. The tables available from the work
done at OSU ESL comprise of the Knowledge base in our case. We have two Knowledge
sources (KSs) for the expert system reasoning. They are ASPOL and ELLIPT.

Please enter the aspect angle polarization data in the following format
     (aspect hh hv vv) :
 e.g ( 120 112 112 112) 3")
 (setq *list1* (read))
 (print "Now enter Engine inlet values for the elliptical KS, in the following
format, FOR ENGINE INLET: (ts te A1 e1 t1) :
                    e.g  (-0.065 0.125 2.731 36 58)")
 (setq *list2* (read))
 (print "Now enter the Tail values for the elliptical KS, in the following
format, FOR TAIL      : (ts te A2 e2 t2) :
         e.g  (0.940 1.135 7.08 5 104)")
 (setq *list3* (read))
 (rdrinp)
 (check-AC *list1*)
 (levelinfo1)
 (ellipt *list2* *list3*)
 (levelinfo2)
 (combine1))
```

```
(defun levelinfo1 ()
 (print "

   ~~~~~~~

   LEVEL 1       THE FOLLOWING HYPOTHESIS HAS BEEN POSTED BY
                  ASPOL  KS:

   ~~~~~~~        KS Name:        ASPOL
                  Features measured:  Aspect angle & polarization
                  Kind:            Direct Measurements
                   Overall Confidence:............. 0.9
                                                   ")
 (print *ASPOLPROB*))

(defun levelinfo2 ()
 (pprint "

   ~~~~~~~

   LEVEL 2       THE FOLLOWING HYPOTHESIS HAS BEEN POSTED BY
                  ELLIPT  KS:

   ~~~~~~~         KS Name:          ELLIPT
                   Features measured:  Elliptical Features
                   Kind:               Derived Measurements
                    Overall Confidence:............ 0.7
                                                   ")
 (print *ELLPROB*))

(defun combine1 ()
 (setq *prd1* (* (funcall 'certratios (car *ASPOLPROB*))
                 (funcall 'certratios (car *ELLPROB*))))
 (setq *prd2* (* (funcall 'certratios (second *ASPOLPROB*))
                 (funcall 'certratios (second *ELLPROB*))))
 (setq *prd3* (* (funcall 'certratios (third *ASPOLPROB*))
                 (funcall 'certratios (third *ELLPROB*))))
 (setq *prd4* (* (funcall 'certratios (fourth *ASPOLPROB*))
                 (funcall 'certratios (fourth *ELLPROB*))))
 (setq *pru5* (* (funcall 'certratios (fifth *ASPOLPROB*))
```

```
                (funcall 'certratios (fifth *ELLPROB*))))
 (combine2))

(defun combine2 ()
 (setq *firstcom* (funcall 'certainties *prd1*))
 (setq *secndcom* (funcall 'certainties *prd2*))
 (setq *thirdcom* (funcall 'certainties *prd3*))
 (setq *forthcom* (funcall 'certainties *prd4*))
 (setq *fifthcom* (funcall 'certainties *prd5*))
 (testcom1))

(defun certratios (inpt)
 (/ inpt (- 1 inpt)))

(defun certainties (inptt)
 (/ inptt (+ 1 inptt)))

(defun rdrinp ()
 (print "

MESSAGE:

Please specify the confidence level for the Object-identification theory

to be acceptable to you: ")
 (setq *userconf* (read)))

(defun confidence-level ()
 (setq *confidence* (max *firstcom* *secndcom* *thirdcom* *forthcom* *fifthcom*))
 (if (>= *confidence* *userconf*) "

MESSAGE:

The confidence in the Most Probable Explaination  was  sufficient enough for

the classification task to be pursued. Hence the classification

information of the AC was output to the USER. " "

WARNING:
```

The confidence in the Most Probable Explaination was NOT sufficient enough for the classification task to be pursued further. Hence even though classification information was output, the USER is warned that the theory might be unreliable. So it should not be pursued any further."

```
))

(defun testcom1 ()
  (cond ((> *firstcom* *secndcom*)
         (if (> *firstcom* *thirdcom*) (testfirst1) (testthird1)))
        (t
         (if (> *secndcom* *thirdcom*) (testsecnd1) (testthird1)))))

(defun testfirst1 ()
  (cond ((> *firstcom* *forthcom*)
         (if (> *firstcom* *fifthcom*) (princonco) (prinb747)))
        (t
         (testforth))))

(defun testthird1 ()
  (cond ((> *thirdcom* *forthcom*)
         (if (> *thirdcom* *fifthcom*) (prinb707) (prinb747)))
        (t
         (testforth))))

(defun testsecnd1 ()
  (cond ((> *secndcom* *forthcom*)
         (if (> *secndcom* *fifthcom*) (prinb727) (prinb747)))
        (t
         (testforth))))

(defun testforth ()
  (if (> *forthcom* *fifthcom*) (prindc10) (prinb747)))

(defun princonco ()
  (print "
```

```
********************************
The identified AC is a  CONCORDE
********************************

The confidence value is:")
  (print *firstcom*)
  (confidence-level))

(defun prinb747 ()
  (print "

**********************************
The identified AC is a  BOEING-747
**********************************

The confidence value is:")
  (print *fifthcom*)
  (confidence-level))

(defun prindc10 ()
  (print "

***********************************
The identified AC is a  DC-10
***********************************

The confidence value is:")
  (print *forthcom*)
  (confidence-level))

(defun prinb707 ()
  (print "

***********************************
The identified AC is a  BOEING-707
***********************************

The confidence value is:")
  (print *thirdcom*)
  (confidence-level))
```

```
(defun prinb727 ()
 (print "

***********************************
The identified AC is a BOEING-727
***********************************

The confidence value is:")
 (print *secndcom*)
 (confidence-level))

;;; **********************End of file for Blackboard*************************
```

APPENDIX
B

SAMPLE RUNS

Sample run I

(presentation)

"

****

****

THIS IS THE *DAI SYSTEM* FOR THE IDENTIFICATION AND CLASSIFICATION OF AIRCRAFTS (ACs).

The ACs which we shall be classifying belong to one of the following five categories, Concorde, Boeing 747, Boeing 727, Boeing 707 and DC10.

****

****

You as a User are simulating the situation data base where the sensors shall feed in the data, and a Program shall extract it in real life situation. The tables available from the work done at OSU ESL comprise of the Knowledge base in our case. We have two Knowledge sources (KSs) for the expert system reasoning. They are ASPOL and ELLIPT.

Please enter the aspect angle polarization data in the following format

(aspect hh hv vv) **:**

e.g (120 112 112 112) "

(125 612 null 612)

"**Now enter Engine inlet values for the elliptical KS, in the following format, FOR ENGINE INLET: (ts te A1 e1 t1) :**

e.g (–0.065 0.125 2.731 36 58)")

(–.3 –.139 22.1 26.7 50)

"**Now enter the Tail values for the elliptical KS, in the following format, FOR TAIL : (ts te A2 e2 t2) :**

e.g (0.940 1.135 7.08 5 104)"

(1.3 1.47 14.5 3 91)

"

MESSAGE:

Please specify the confidence level for the Object–identification theory

to be acceptable to you: "

0.9

"

********* Level I KS: ASPOL.************

It is possible that data out of bounds might have been given at this stage, but it is not of significant interest to me since no decision about the proof of identity of the object has yet been taken. However very soon the identity of the Object shall be established."

"

****

The Object is not a Boeing–747

***********************************,

**Please enter the Polarization

Values (120 hh hv vv) for Aspect angle 120:"

(120 112 112 112)

"Now enter those for Aspect angle 130 (130 hh hv vv):"

(130 112 112 112)

"Now enter those for Aspect angle 135 (135 hh hv vv):"

(135 112 113 112)

"

ERROR, Data out of Bounds

MESSAGE:

This Knowledge source would not be able to generate and post a hypothesis based on the data you have supplied. If you do not have sufficient data please reply a YES to the following question (and the identification and classification shall proceed only on the basis of the remaining KS's) however, if you want to reenter data correctly, after answering a NO to the question, please enter it again. "

"

Message:

Do you have insufficient or inaccurate data?"

<u>no</u>

"

****

****The Object is not a Boeing-747****

***********************************,

**Please enter the Polarization

Values (120 hh hv vv) for Aspect angle 120:"

<u>(120 112 112 112)</u>

"Now enter those for Aspect angle 130 (130 hh hv vv):"

<u>(130 112 112 112)</u>

"Now enter those for Aspect angle 135 (135 hh hv vv):"

<u>(135 112 112 112)</u>

"

** The Object is not a DC-10 OR BOEING-747 **

But I shall try checking if it is one of BOEING-707, BOEING-727 and CONCORDE"

"

MESSAGE,

Is Polarization data available for aspect angles 10 and 15?

If any one or none of them is available I have insufficient data. The identification and classification shall then proceed on the basis of other KS's. Answer a NO for that case. Please answer YES if polarization values for both of them are available:"

<u>yes</u>

"

**This is to check if it is a Boeing-707 or Boeing-727 or Concorde, Please enter the values of polarization for Aspect

angle 15, e.g (15 hh hv vv):"

<u>(15 112 null 112)</u>

"Now enter those for Aspect 10, e.g (10 hh hv vv):"

(10 112 113 111)

"

ERROR, Data out of Bounds

MESSAGE:

This Knowledge source would not be able to generate and post a hypothesis based on the data you have supplied. If you do not have sufficient data please reply a YES to the following question (and the identification and classification shall proceed only on the basis of the remaining KS's) however, if you want to reenter data correctly, after answering a NO to the question, please enter it again. "

"

Message:

Do you have insufficient or inaccurate data?"

yes

"

~~~~~~~~

LEVEL 1 **THE FOLLOWING HYPOTHESIS HAS BEEN POSTED BY ASPOL KS:**

~~~~~~~~

KS Name: ***ASPOL***

Features measured: Aspect angle & polarization

Kind: ***Direct Measurements***

Overall Confidence:............ 0.9

"

The confidence in the *BOEING 747* **is the highest and is: 0.7. The confidence in each of the remaining AC's is the following, their order being (Concorde Boeing727 Boeing707 DC10 and Boeing747):**

"

(0.242 0.01 0.13599999 0.242 0.7)

"

"

"

LEVEL 2 **THE FOLLOWING HYPOTHESIS HAS BEEN POSTED BY ELLIPT KS:**

KS Name: ***ELLIPT***

Features measured: ***Elliptical Features***

Kind: ***Derived Measurements***

Overall Confidence:............ 0.7

"

(0.242 0.01 0.13599999 0.242 0.7)

"

****

The identified AC is a ***BOEING–747***

****

The confidence value is:"

0.023026315

"

WARNING:

The confidence in the Most Probable Explanation was NOT sufficient enough for the classification task to be pursued further. Hence even though classification information was output, the USER is warned that the theory might be unreliable. So it should not be pursued any further."

Sample run II

(presentation)

****

****

THIS IS THE *DAI SYSTEM* FOR THE IDENTIFICATION AND CLASSIFICATION OF AIRCRAFTS (AC*s*).

The ACs which we shall be classifying belong to one of the following five categories, Concorde, Boeing 747, Boeing 727, Boeing 707 and DC10.

****

****

You as a User are simulating the situation data base where the sensors shall feed in the data, and a Program shall extract it in real life situation. The tables available from the work done at OSU ESL comprise of the Knowledge base in our case. We have two Knowledge sources (KSs) for the expert system reasoning. They are ASPOL and ELLIPT.

Please enter the aspect angle polarization data in the following format

(aspect hh hv vv) :

e.g (120 112 112 112) "

(10 112 112 112)

"Now enter Engine inlet values for the elliptical KS, in the following format, **FOR ENGINE INLET: (ts te A1 e1 t1)** :

e.g (–0.065 0.125 2.731 36 58)")

(–.12 .095 21.4 176.9)

"Now enter the Tail values for the elliptical KS, in the following format, **FOR TAIL : (ts te A2 e2 t2)** :

e.g (0.940 1.135 7.08 5 104)"

(.95 1.13 6.5 8 96)

MESSAGE:

Please specify the confidence level for the Object–identification theory

to be acceptable to you: "
0.9

"

********* Level I KS: ASPOL.************

It is possible that data out of bounds might have been given
at this stage, but it is not of significant interest to me since no
decision about the proof of identity of the object has yet been taken.
However very soon the identity of the Object shall be established."
"

****

The Object is not a Boeing–747

****

**Please enter the Polarization
Values (120 hh hv vv) for Aspect angle 120:"
(120 112 null 112)
"Now enter those for Aspect angle 130 (130 hh hv vv):"
(130 112 null 112)
"Now enter those for Aspect angle 135 (135 hh hv vv):"
(135 112 null 12)
"

ERROR, Data out of Bounds

MESSAGE:

This Knowledge source would not be able to generate and post a
hypothesis based on the data you have supplied. If you do not have
sufficient data please reply a YES to the following question (and the
identification and classification shall proceed only on the basis of

the remaining KS's) however, if you want to reenter data correctly,

after answering a NO to the question, please enter it again. "

"

Message:

Do you have insufficient or inaccurate data?"

no

"

****

The Object is not a Boeing–747

************************************,

**Please enter the Polarization

Values (120 hh hv vv) for Aspect angle 120:"

<u>(120 112 null 112)</u>

"Now enter those for Aspect angle 130 (130 hh hv vv):"

<u>(130 112 null 112)</u>

"Now enter those for Aspect angle 135 (135 hh hv vv):"

<u>(135 112 null 112)</u>

"

****

The Object is a DC–10

****

These are the confidence values of the ACs, their order is,

(Concord Boeing727 Boeing707 DC10 Boeing747): "

(0.2 0.2 0.2 0.9 0.3)

"

~~~~~~~

LEVEL 1 **THE FOLLOWING HYPOTHESIS HAS BEEN POSTED BY ASPOL KS:**

~~~~~~~ ***KS Name:*** ***ASPOL***

Features measured: Aspect angle & polarization

Kind: ***Direct Measurements***

Overall Confidence:............ 0.9

"

(0.2 0.2 0.2 0.9 0.3)

"

The confidence in the *BOEING 707* is the highest and is: 0.7. The confidence in each of the remaining AC's is the following, their order being (Concorde Boeing727 Boeing707 DC10 and Boeing747):

"

(0.348 0.232 0.7 0.232 0.242)

"

---"

LEVEL 2	**THE FOLLOWING HYPOTHESIS HAS BEEN POSTED BY ELLIPT KS:**	
	KS Name:	***ELLIPT***
	Features measured:	***Elliptical Features***
	Kind:	***Derived Measurements***
	Overall Confidence:............ 0.7	

"

(0.348 0.232 0.7 0.232 0.242)

"

****

The identified AC is a *DC-10*

****

The confidence value is:"

0.7310924

"

WARNING:

The confidence in the Most Probable Explanation was NOT sufficient enough for

the classification task to be pursued further. Hence even though classification information was output, the USER is warned that the theory might be unreliable. So it should not be pursued any further."

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